Interactive Image-Based Rendering using Feature Globalization

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ACM SIGGRAPH 2003 Symposium on Interactive 3D Graphics

Image-Based Rendering (IBR)

- Create photorealistic models of real-world environments by resampling images from a (large) set of pictures

Frank Lloyd Wright
Fallingwater House, PA

Thomas Jefferson
Monticello, VA

Inside Independence
Hall, Philadelphia, PA

IBR Components

- Capture
- Representation
- Resampling

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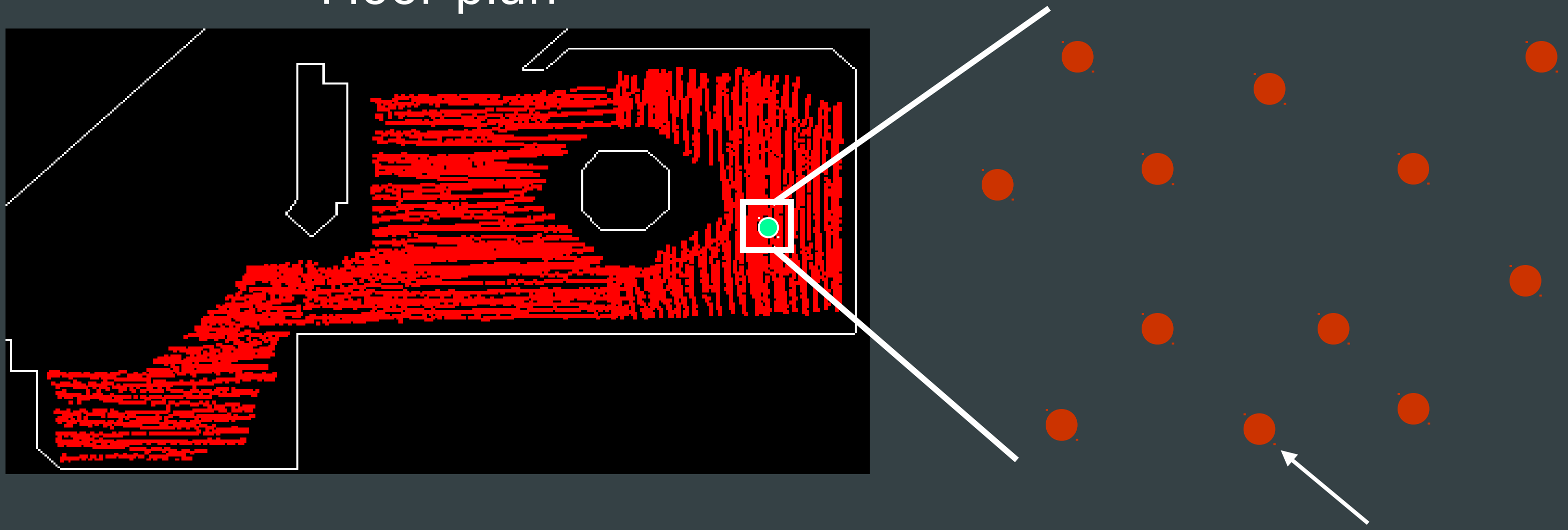
- **Capture**
- Representation
- Resampling



[Aliaga02]

IBR Components

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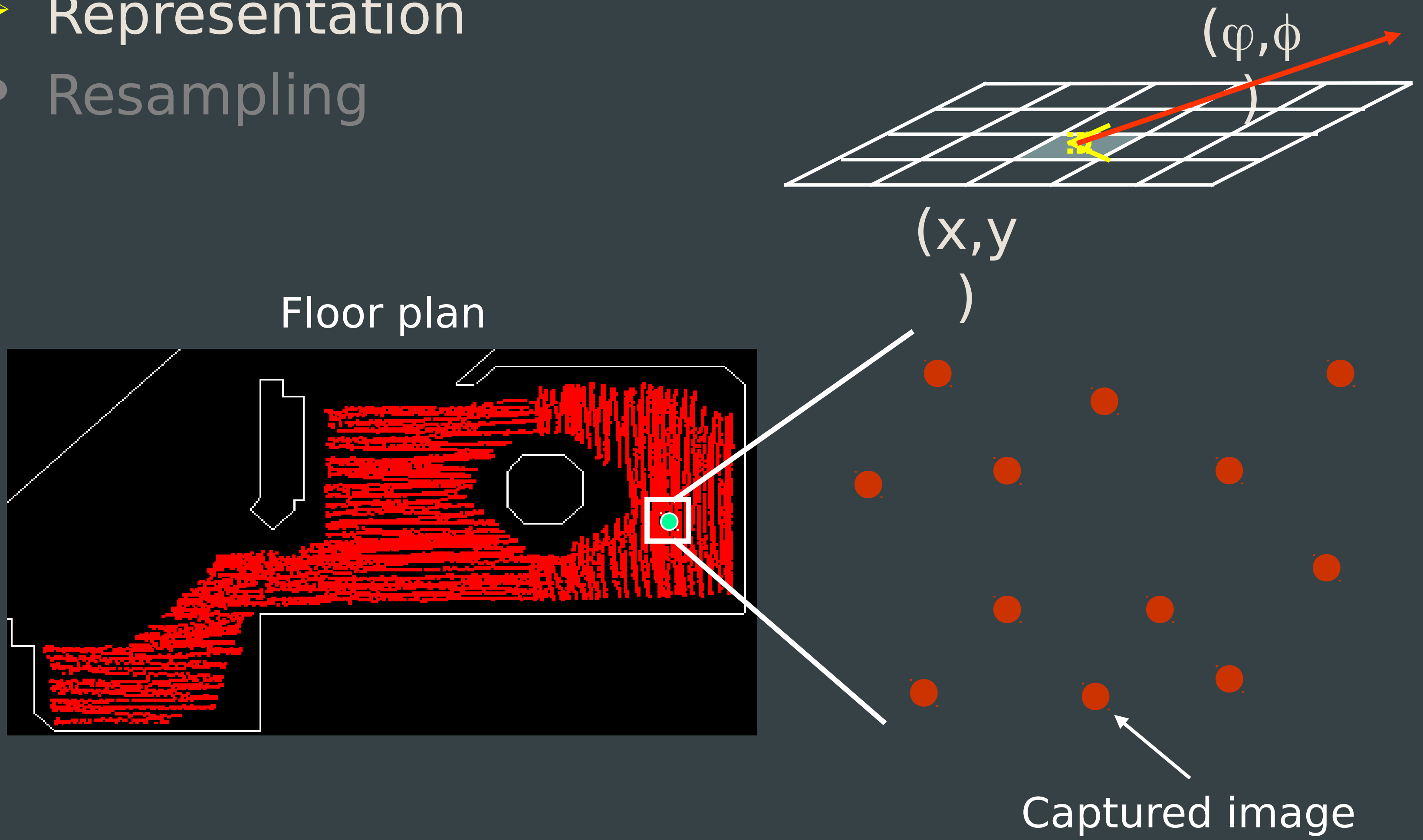
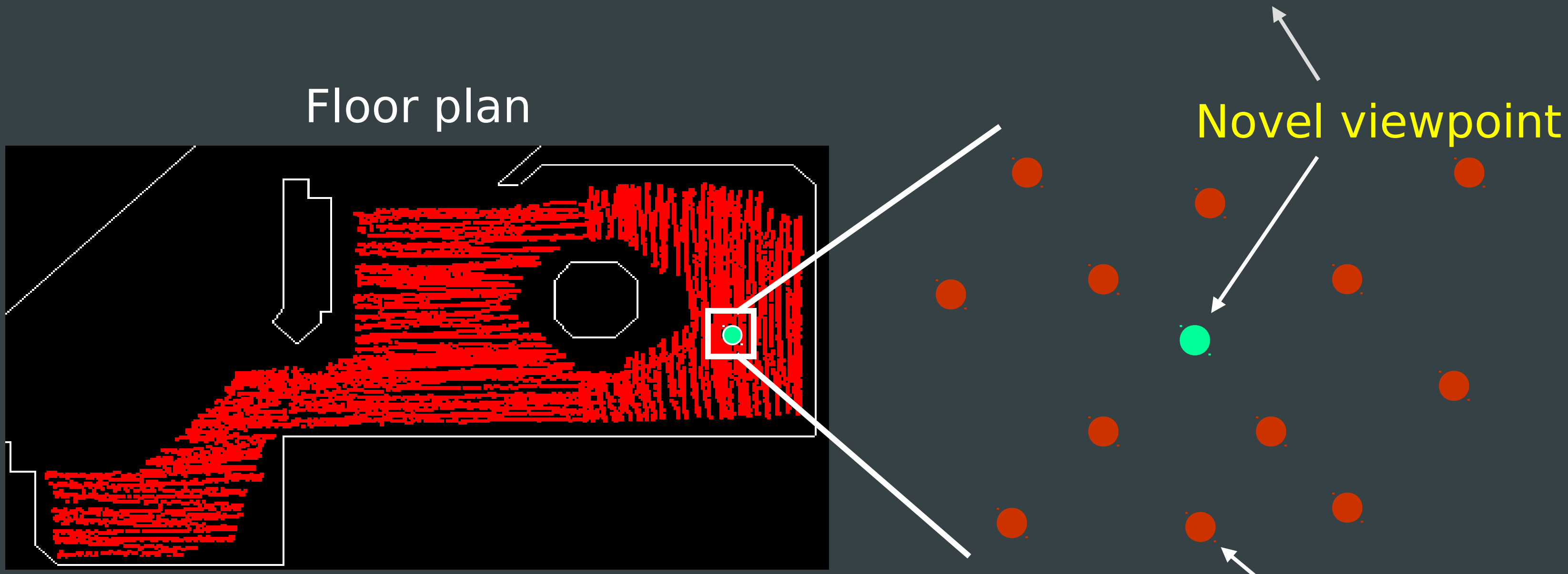


IBR Components

- Capture
- Representation
- Resampling

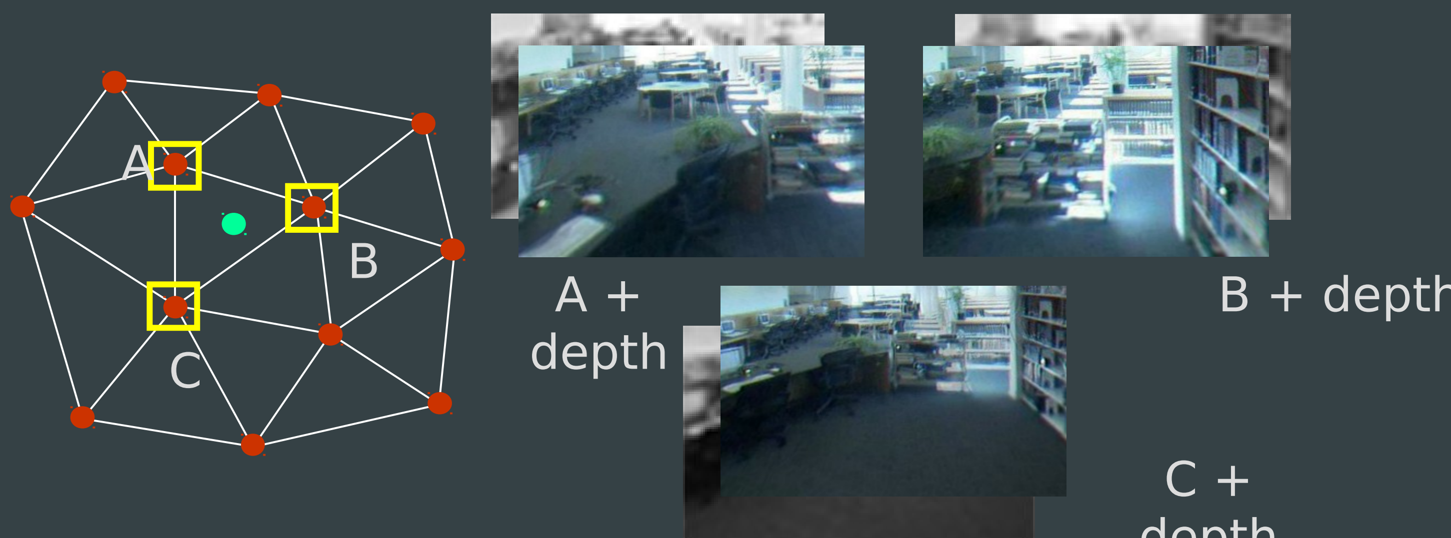
???  ???

Floor plan



Possible Approaches

- Ideal image warping
  - Requires dense correspondence or depth for every pixel
- Proxy-based warping
  - Quality depends on accuracy of proxy
- Feature-based warping
  - Image reconstruction depends on having sufficient features



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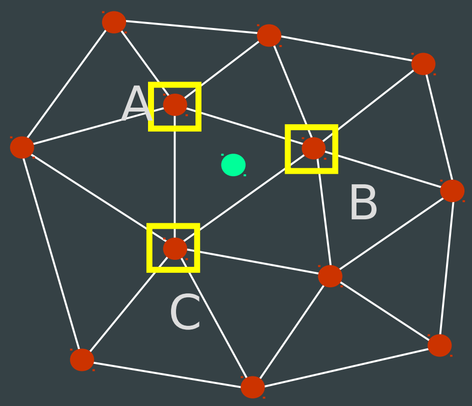

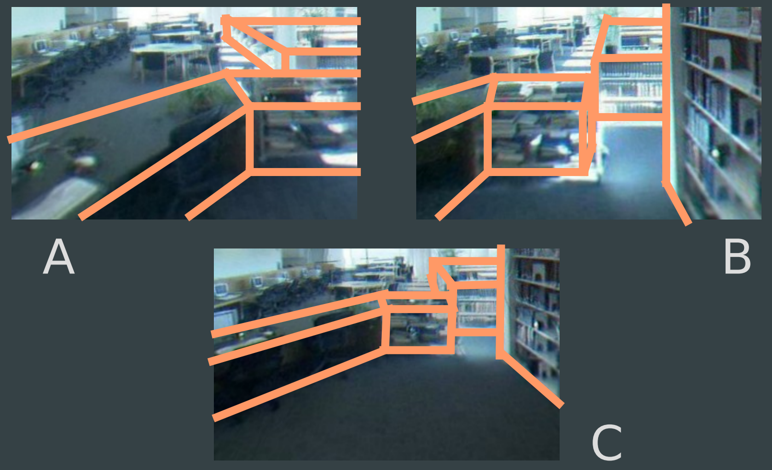

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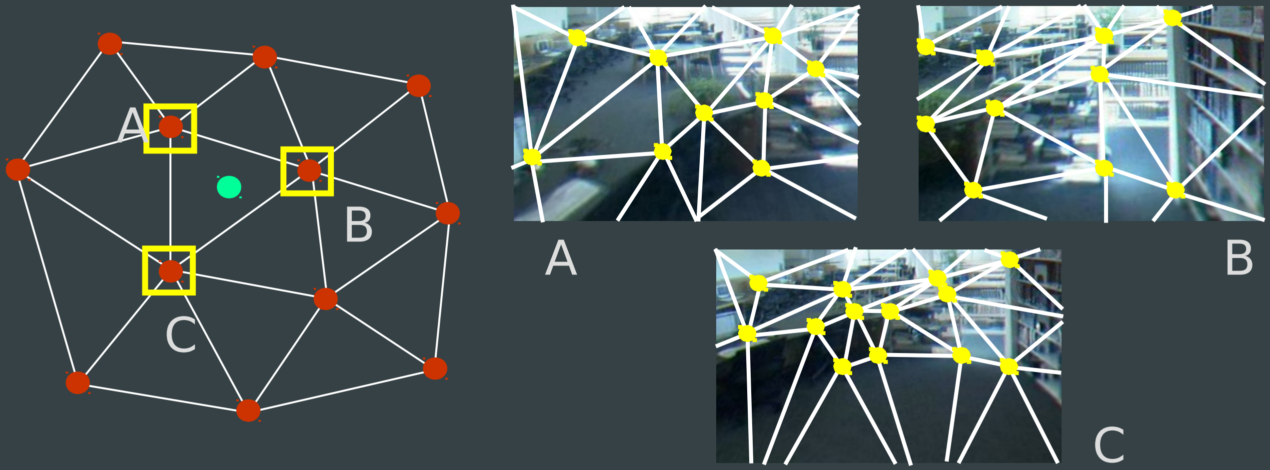

Possible Approaches

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  - Requires dense correspondence or depth for every pixel
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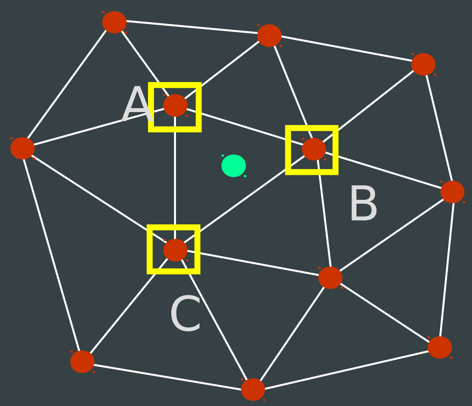
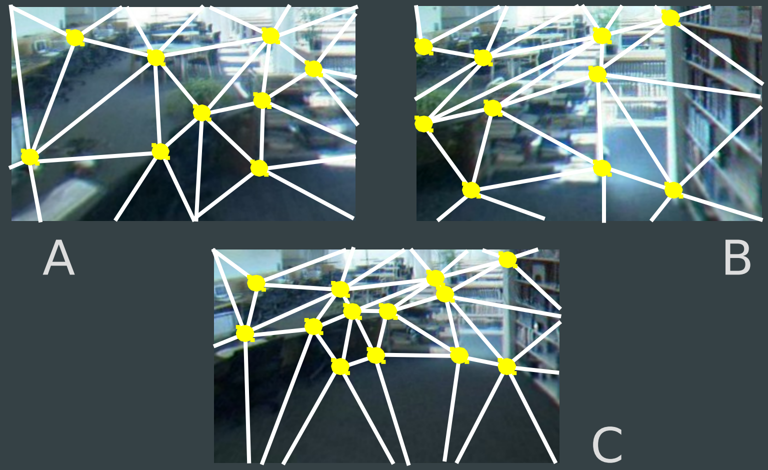
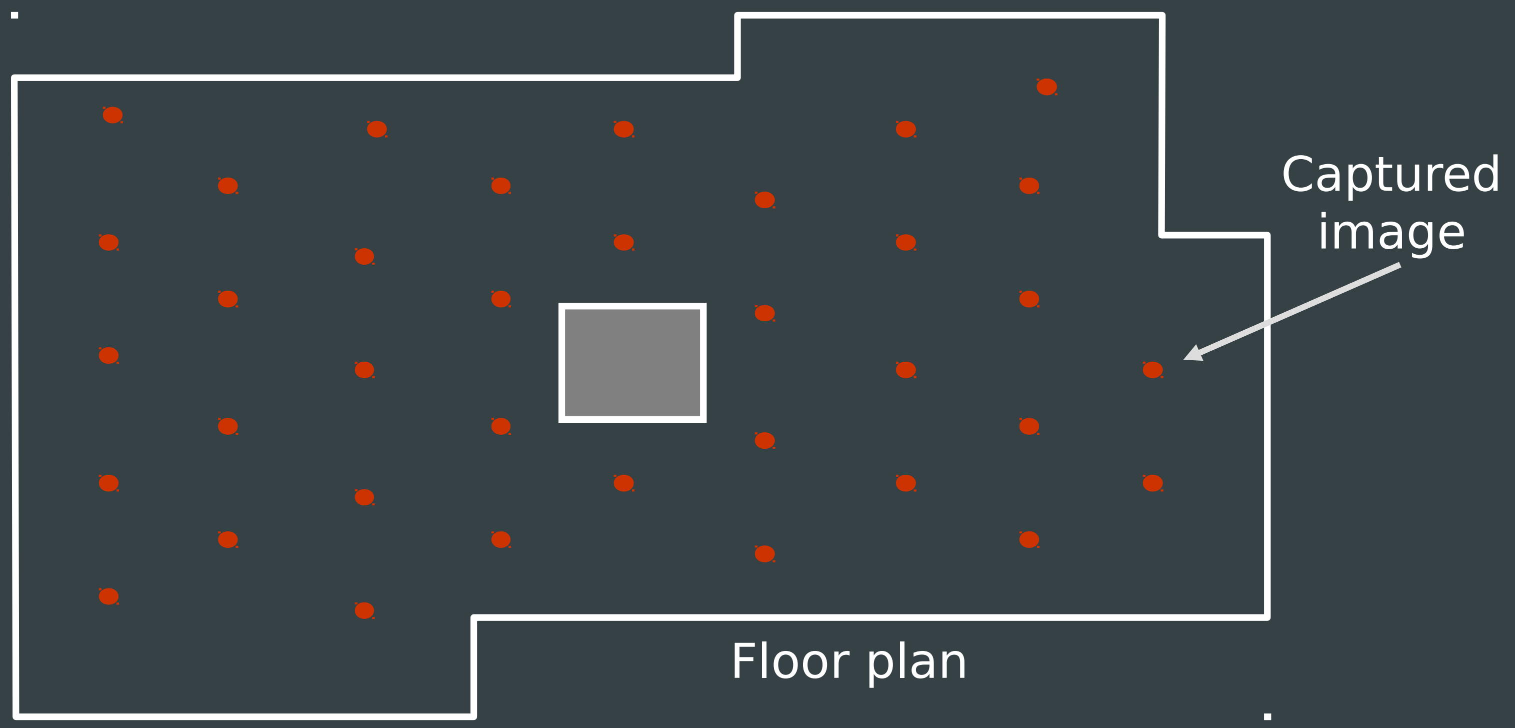
- Feature-based warping
  - ADVANTAGE: No a priori model needed, sharp details preserved, hides calibration errors





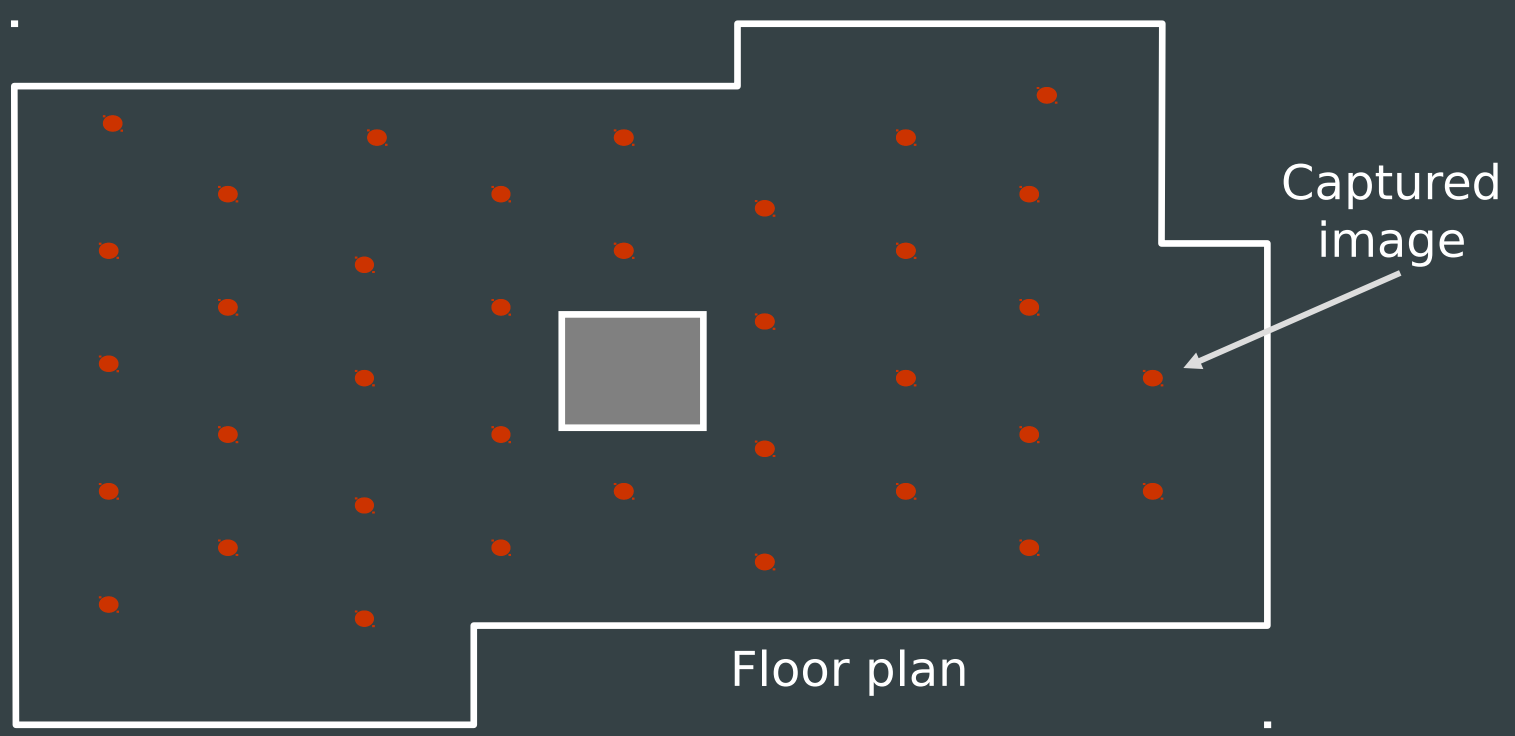
Feature-based Warping: Goal

- Given a collection of images, compute a large set of consistent features across the images



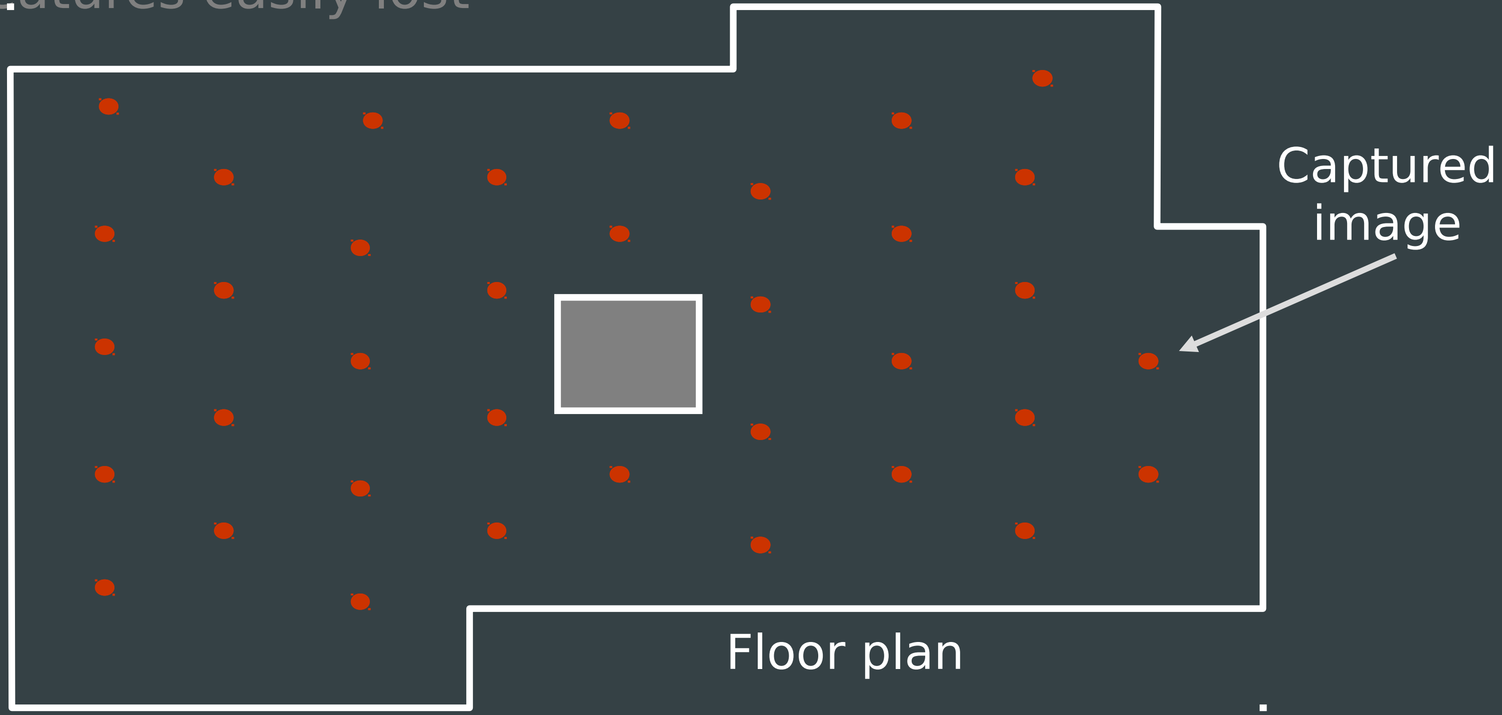
Feature-based Warping: Challenge

- Overcome the limitations of feature detection, feature tracking, and correspondence to create a large set of consistent features



Feature-based Warping: Previous Work

- Use human intervention [McMillan95]
  - Very time consuming, do not scale to large environments
- Track images along video sequences [Pollefeys98]
  - Features easily lost



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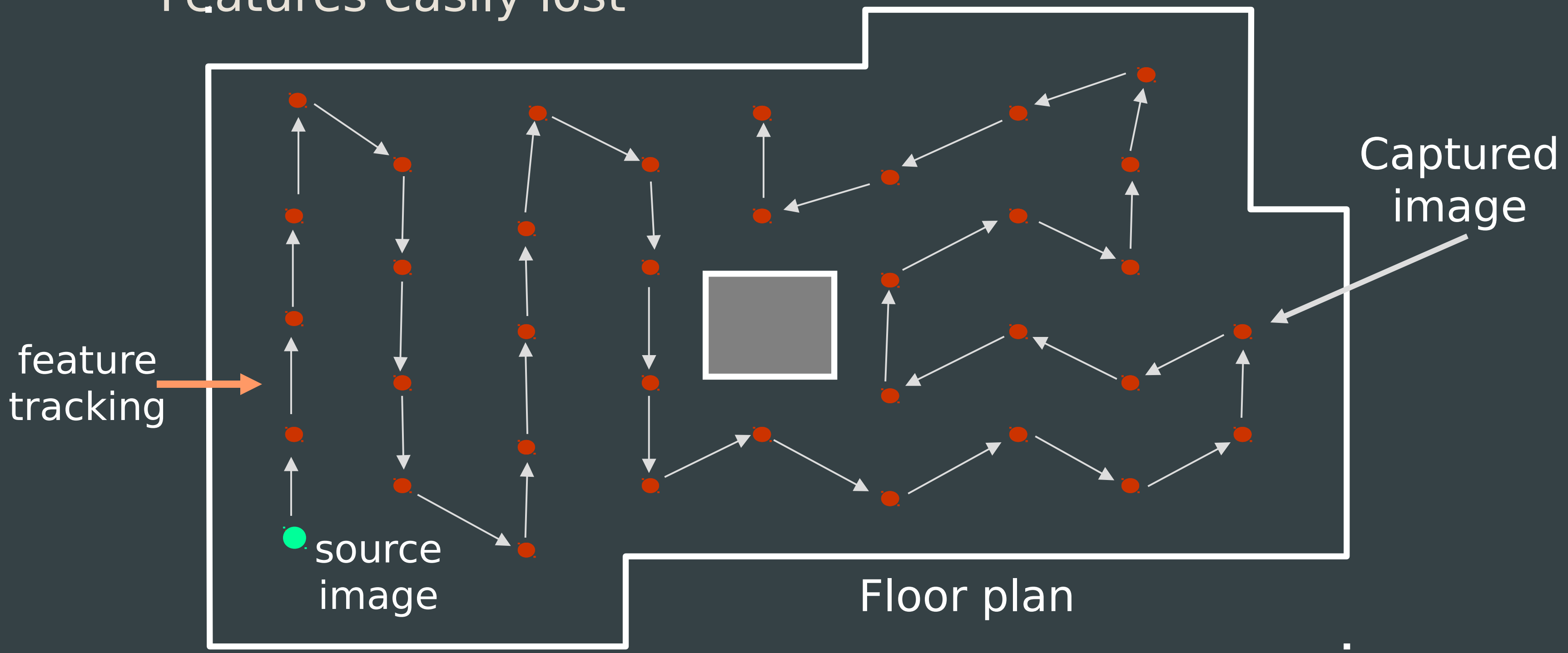
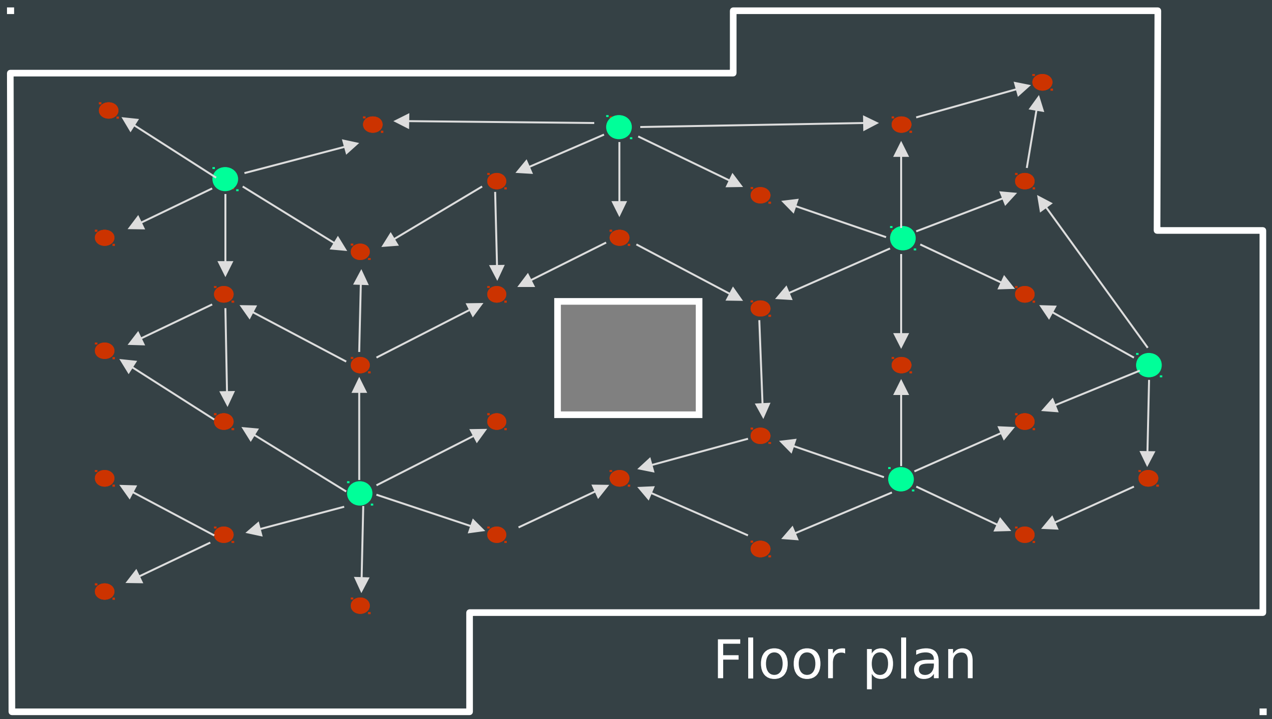


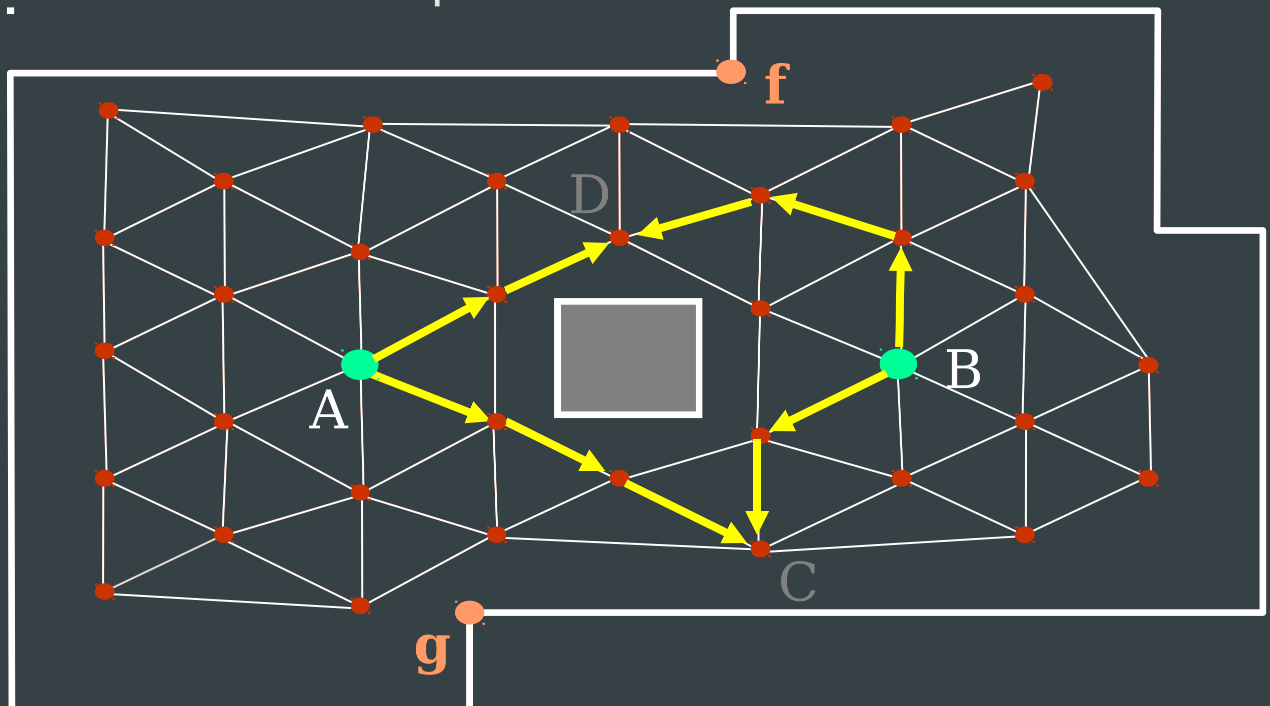
Our Approach: Feature Globalization

- Divide and conquer: create many source images, track radially outward, perform feature matching and globally consistent relabeling to create global feature set



Our Approach: Feature Globalization

- Key property is correspondences are identified if two features match along any viewpoint path between images
  - Finds more correspondences and across a wider range



Feature Globalization Benefits

- Global
  - Far apart images can still have large set of common features
  - Supports rendering from images currently loaded from disk
- Consistent
  - No single feature has two global labels
- Automatic
  - Supports large environments
- Efficient
  - Able to control the tradeoff of amount of globalization and work

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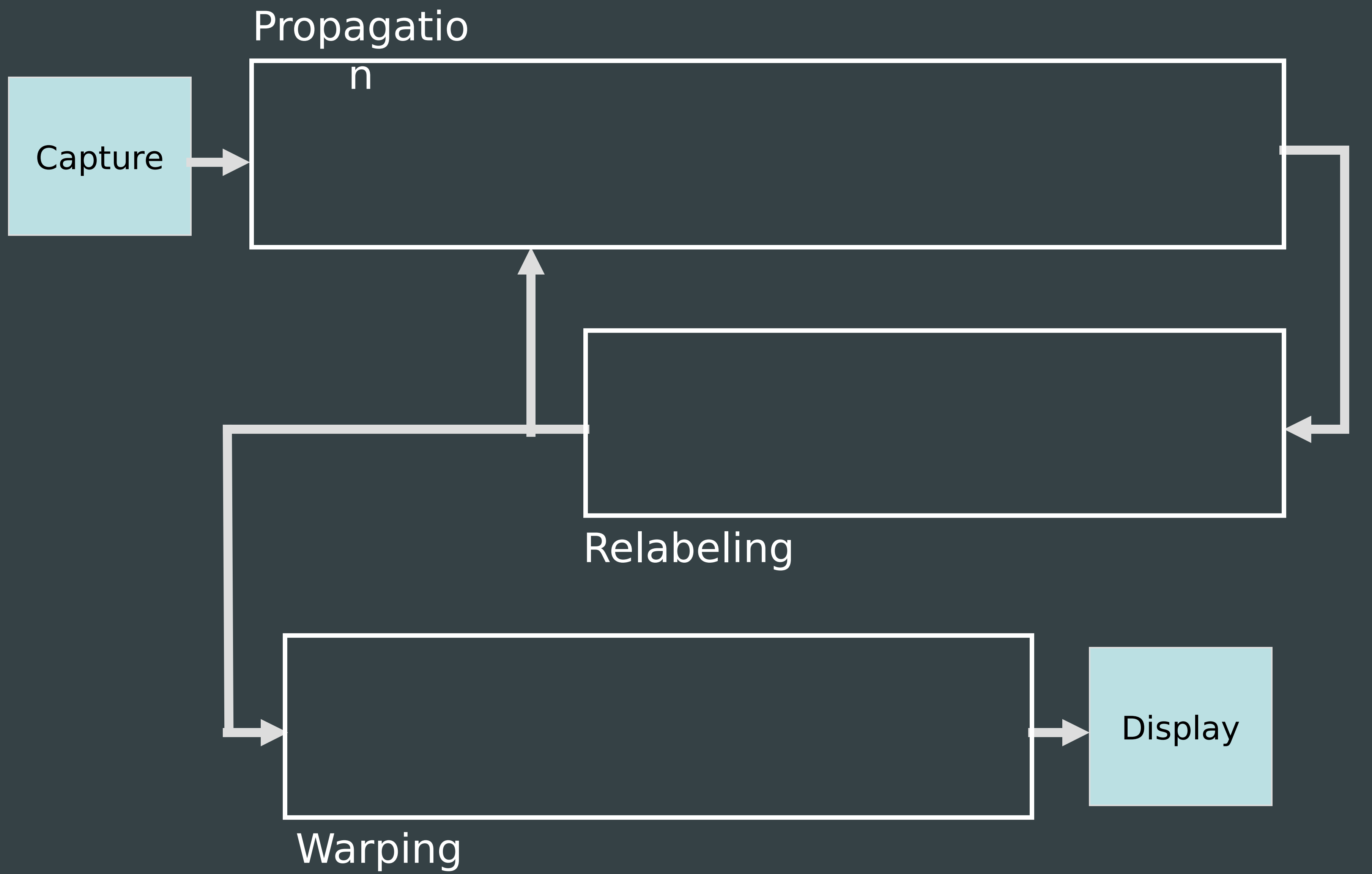
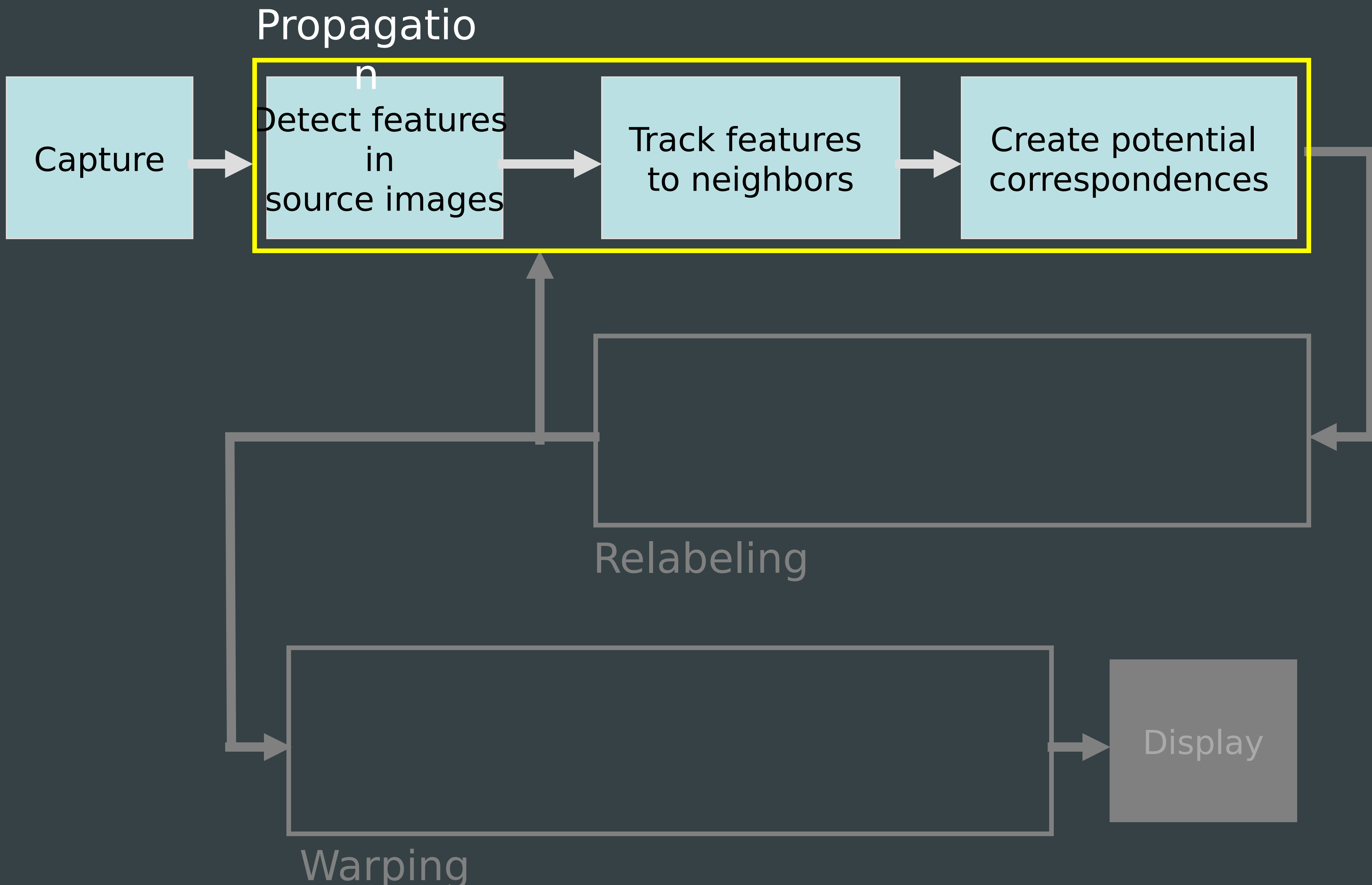
Feature Globalization Algorithm

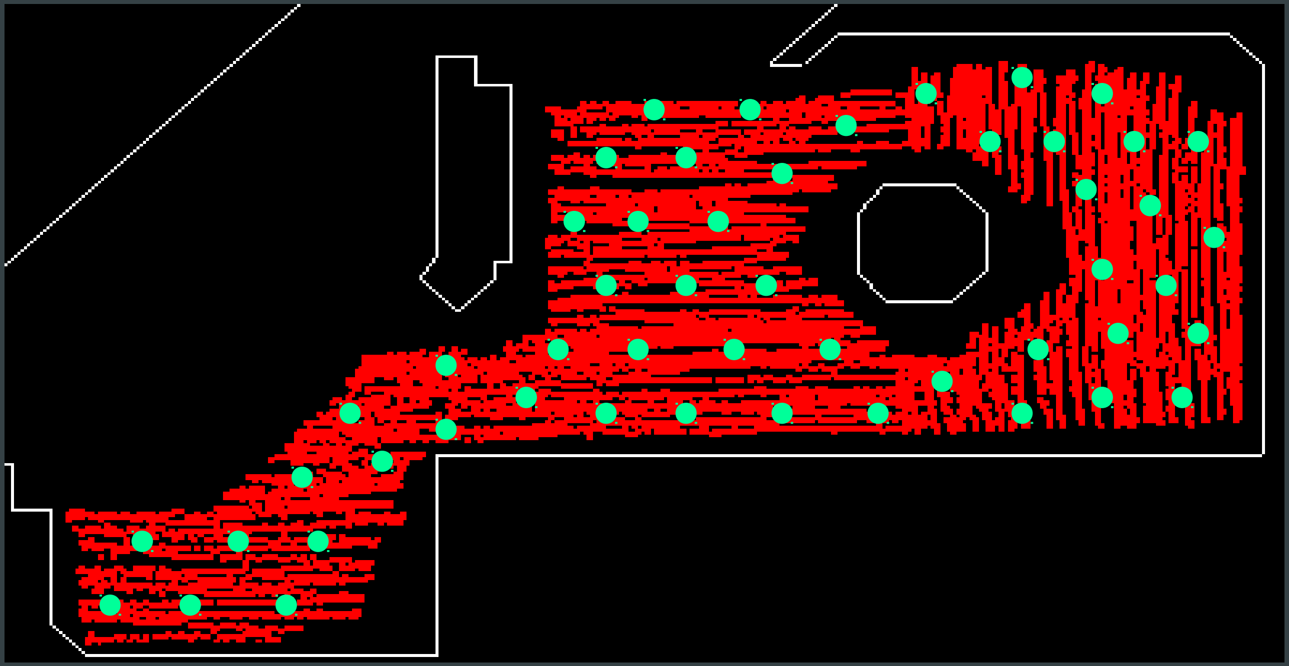


Feature Globalization Algorithm



Propagation

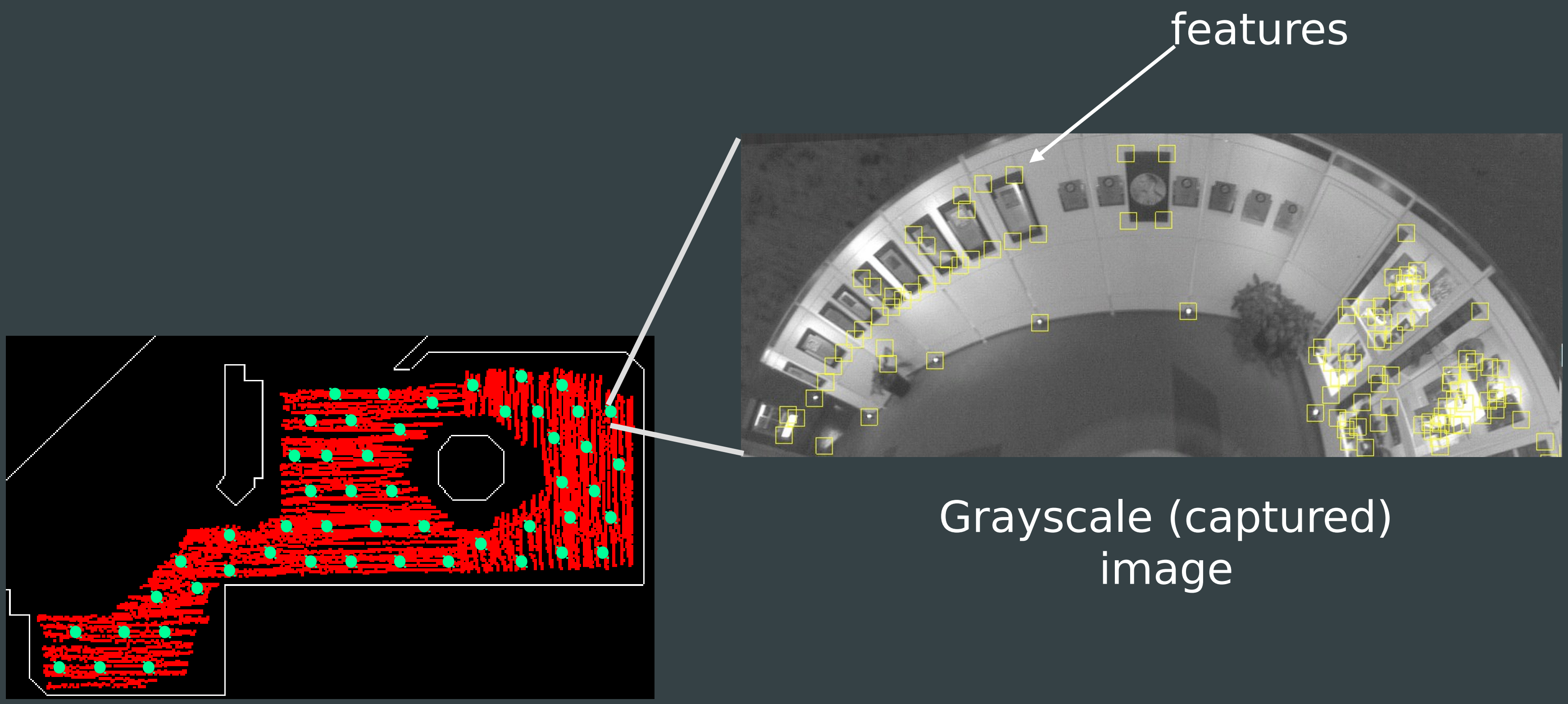
- Choose a set of source images throughout the dataset



Each red-dot is a captured image
Each green dot is a source image

Propagation

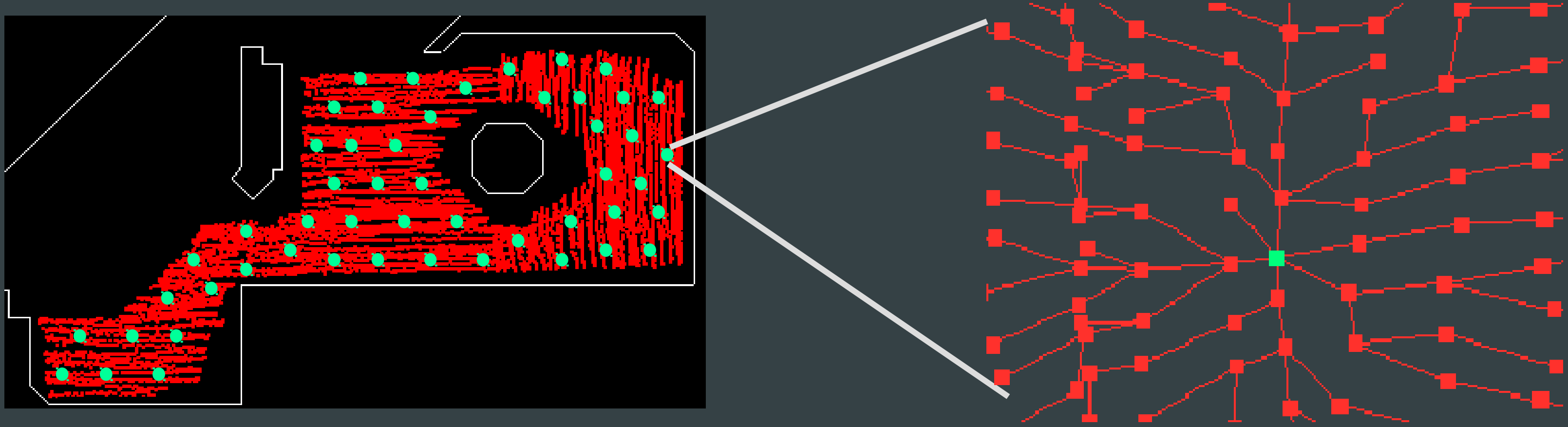
- Detect features in every source image
  - Our "corner" features lie at the intersection of nearly orthogonal edges [Shi94]



Grayscale (captured) image

Propagation

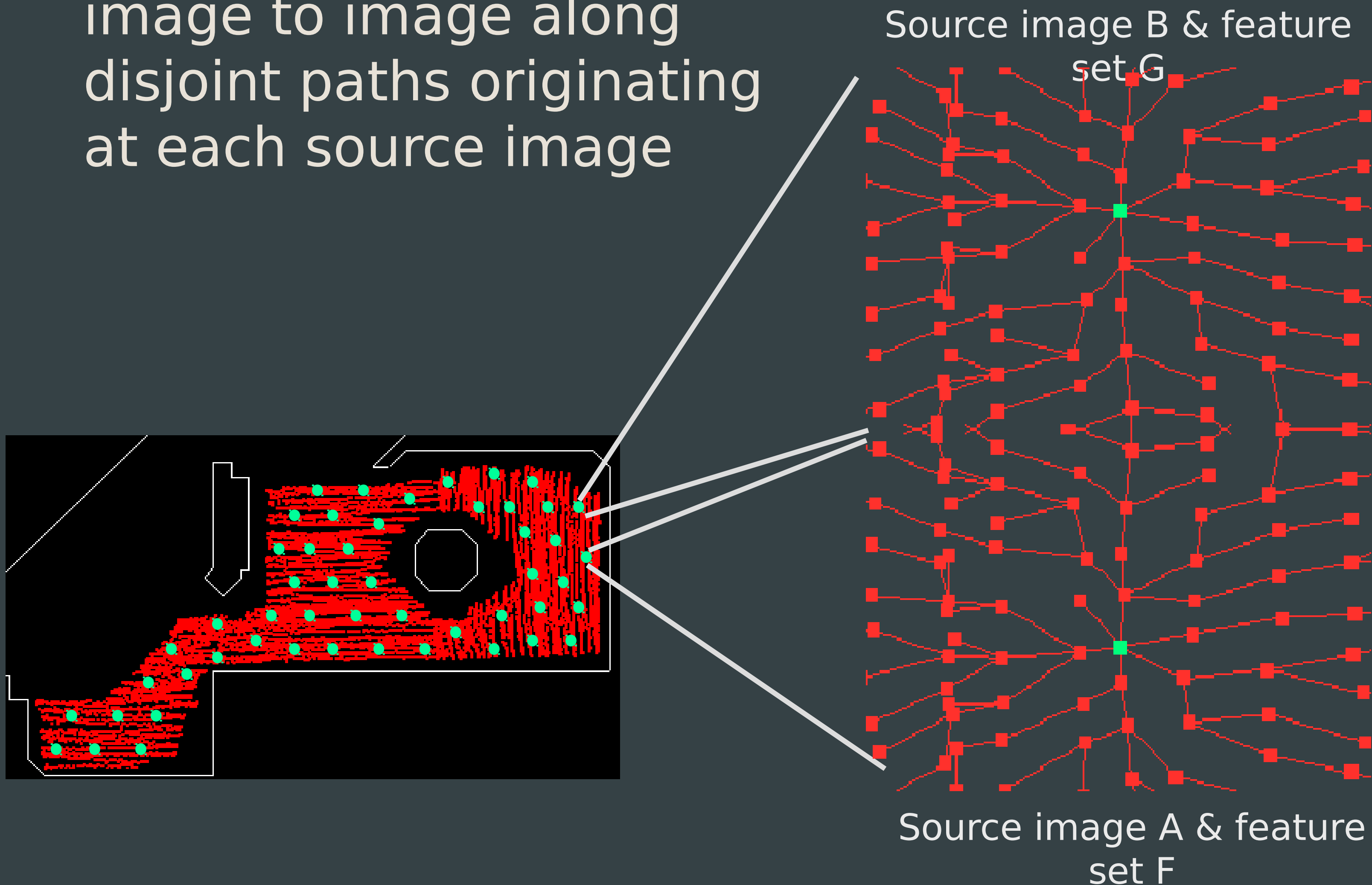
- Track features from image to image along disjoint paths originating at each source image



Source image A & feature set F

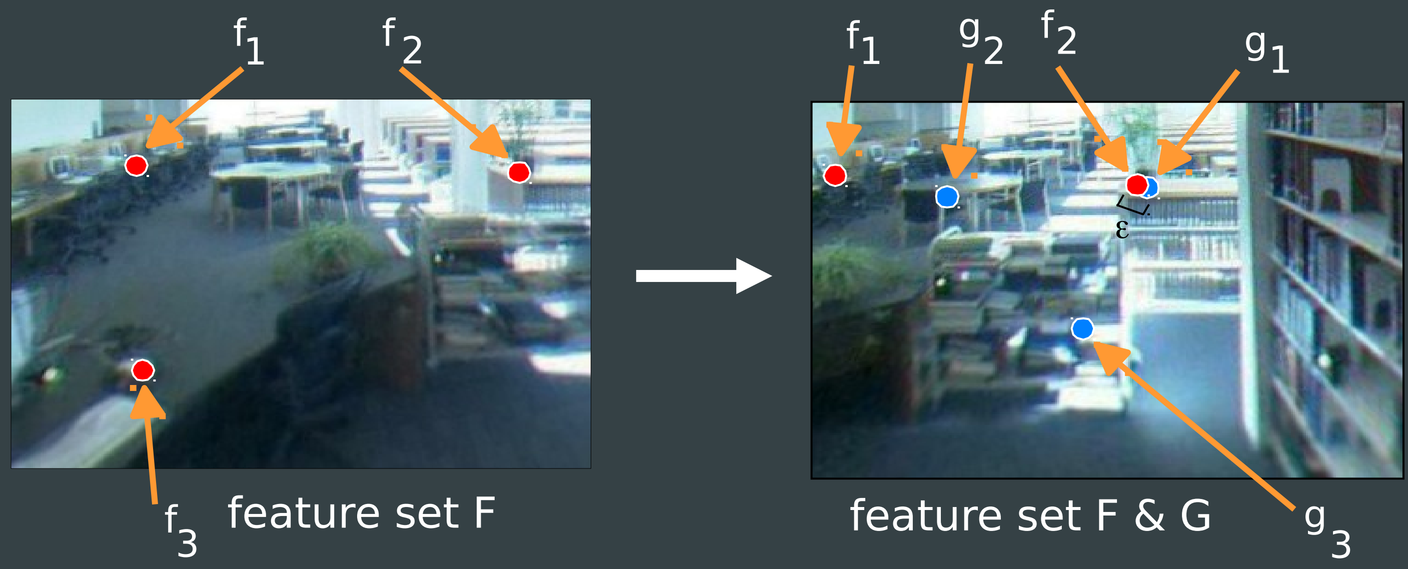
Propagation

- Track features from image to image along disjoint paths originating at each source image



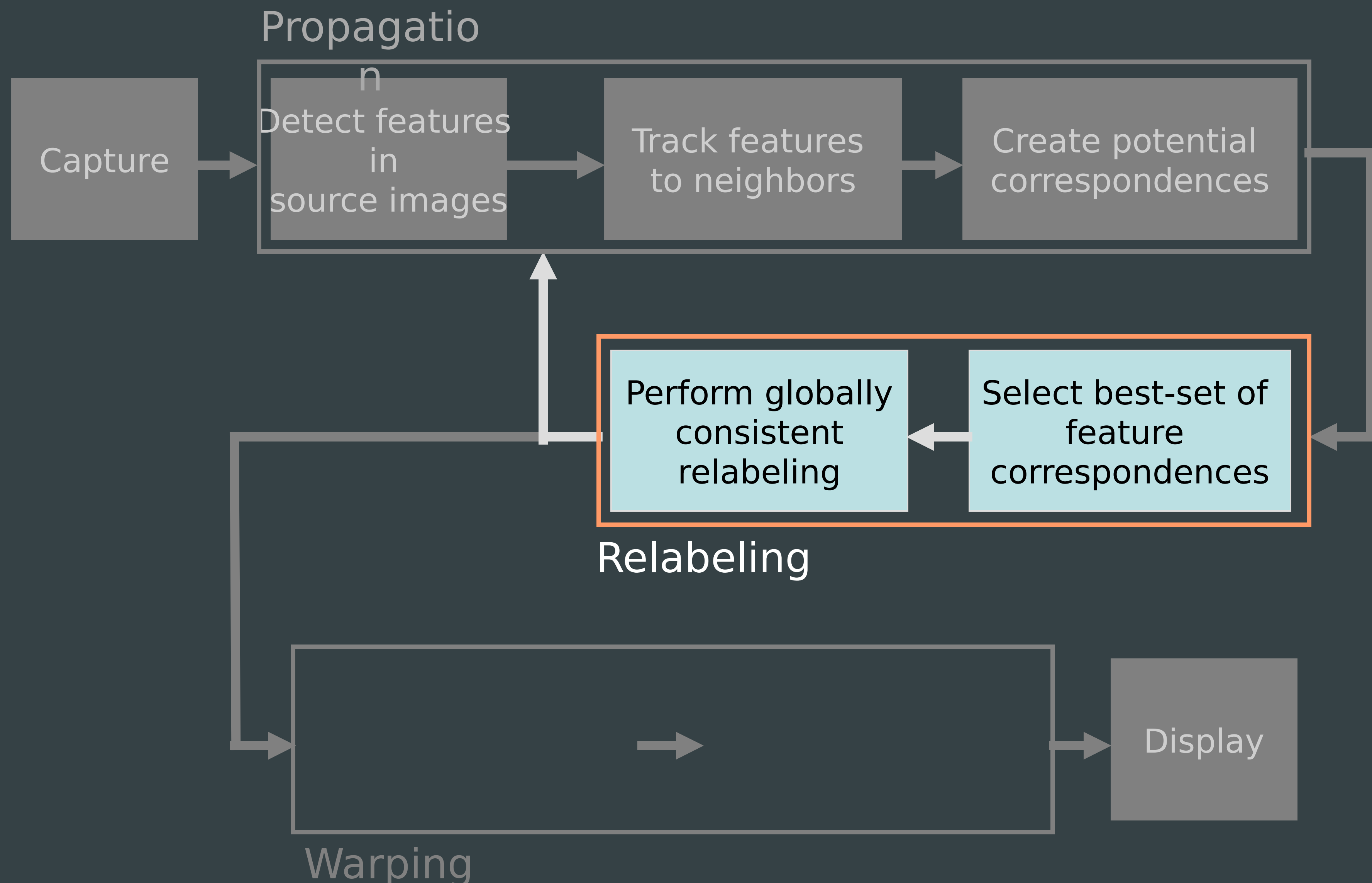
Propagation

- Create candidate correspondences between features from different source images that track to the same location and satisfy correlation and quality criteria



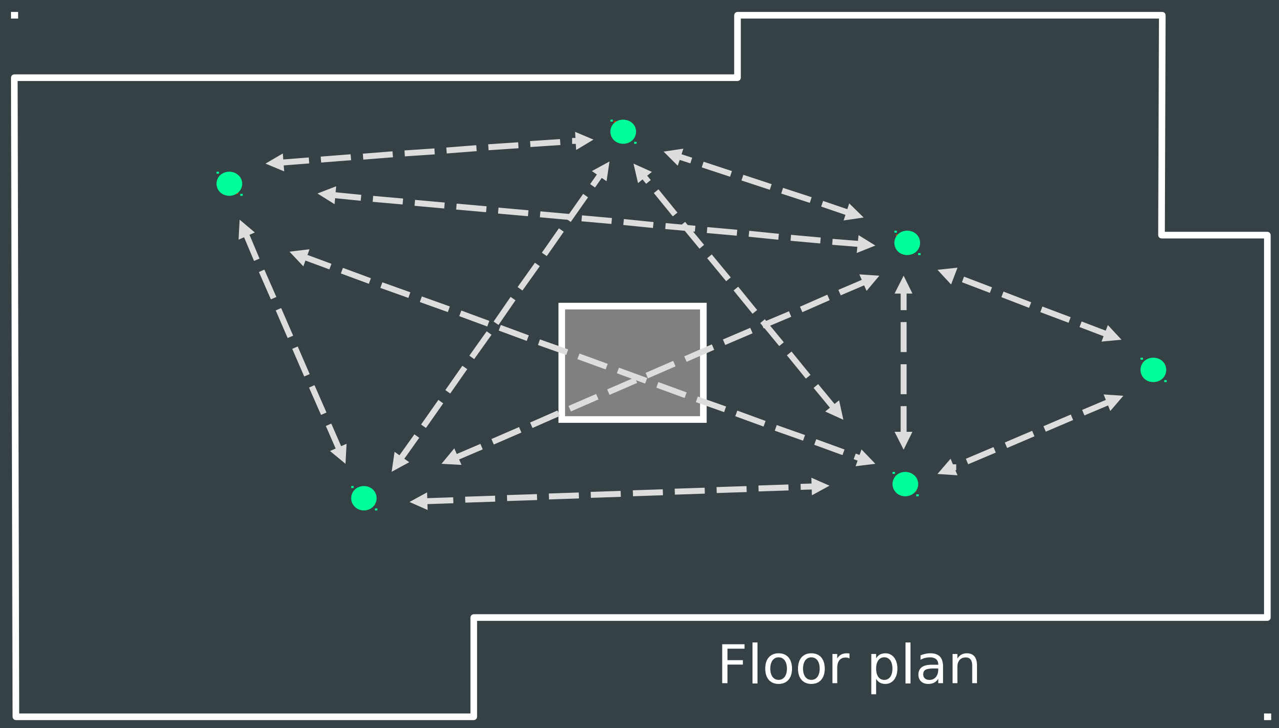
e.g., $f_2 = g_1$ is a potential correspondence…

Feature Globalization Algorithm



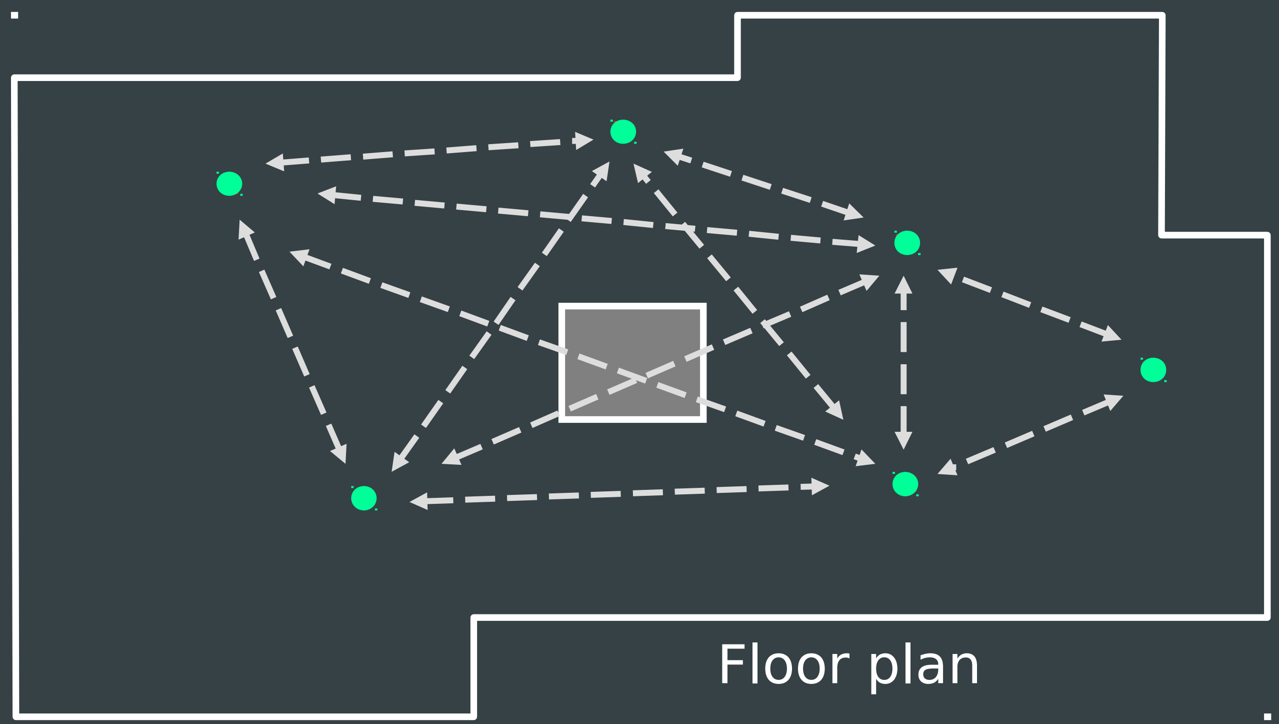
Relabeling

- We have tracked features from each source image outwards and created all potential correspondences…



Relabeling

- The task is to choose the "best" subset of consistent correspondences between features of the source images



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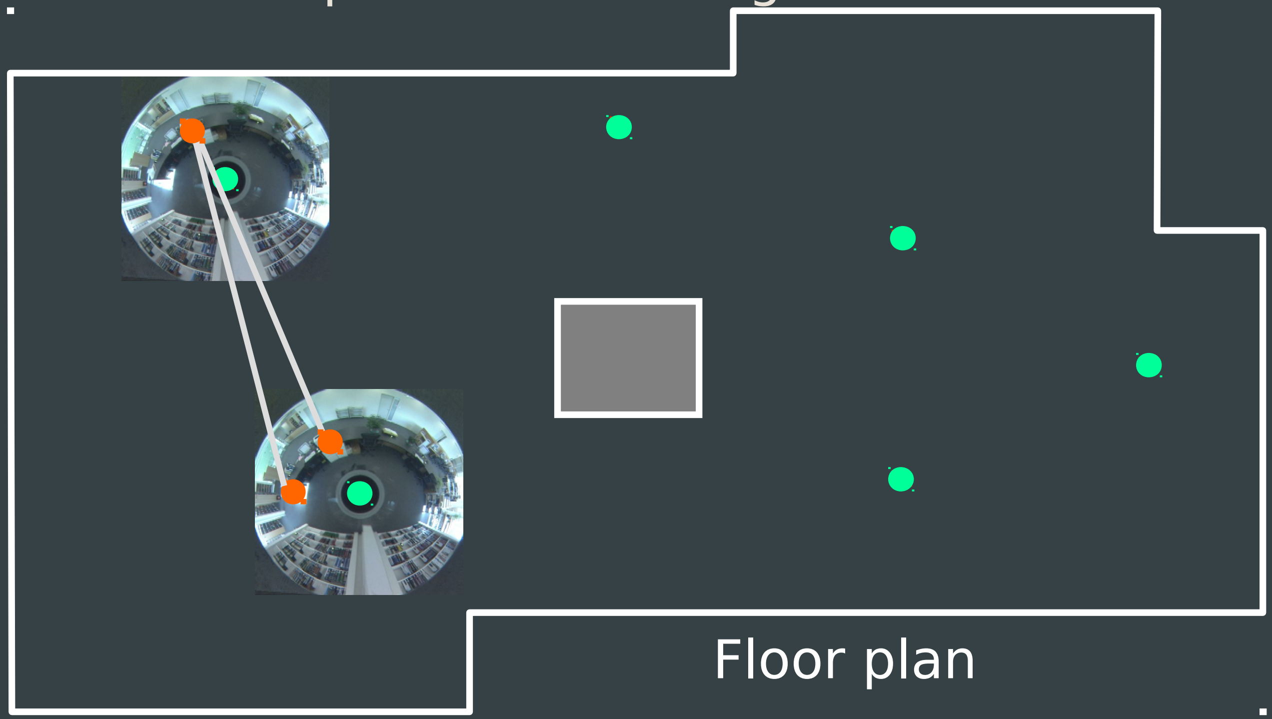
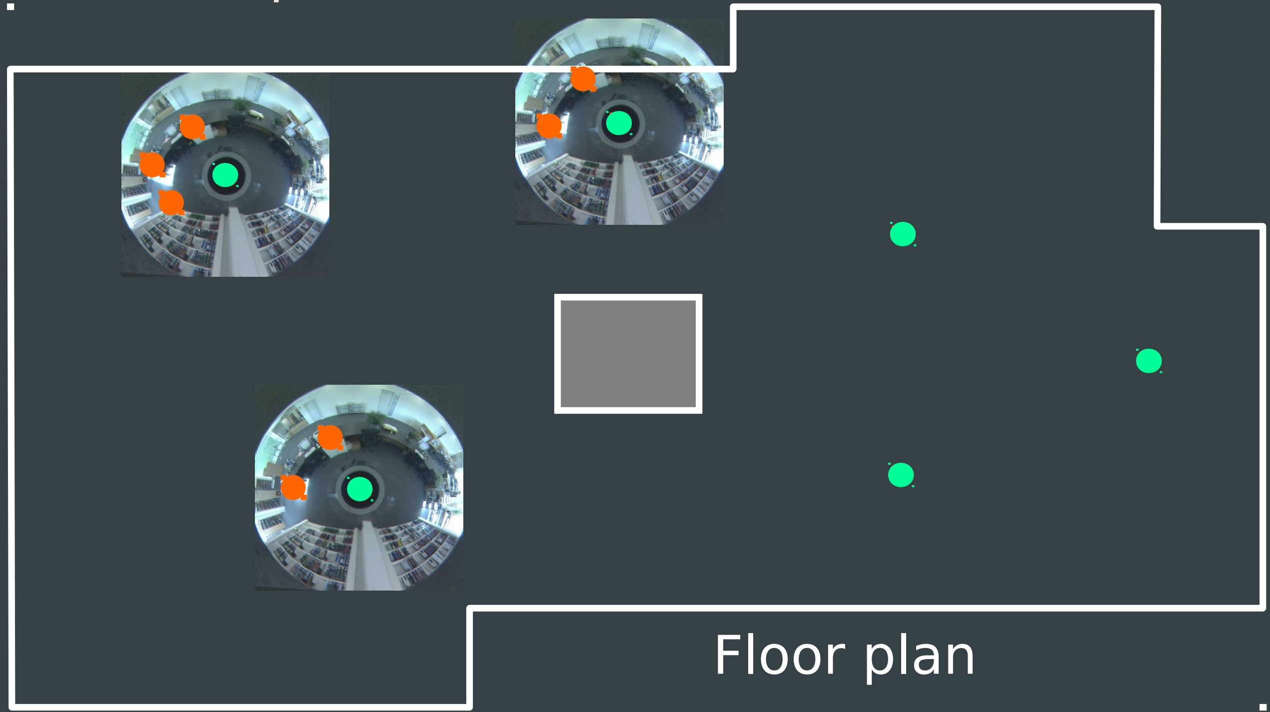
  - Consistent implies that no single feature has two labels



Relabeling

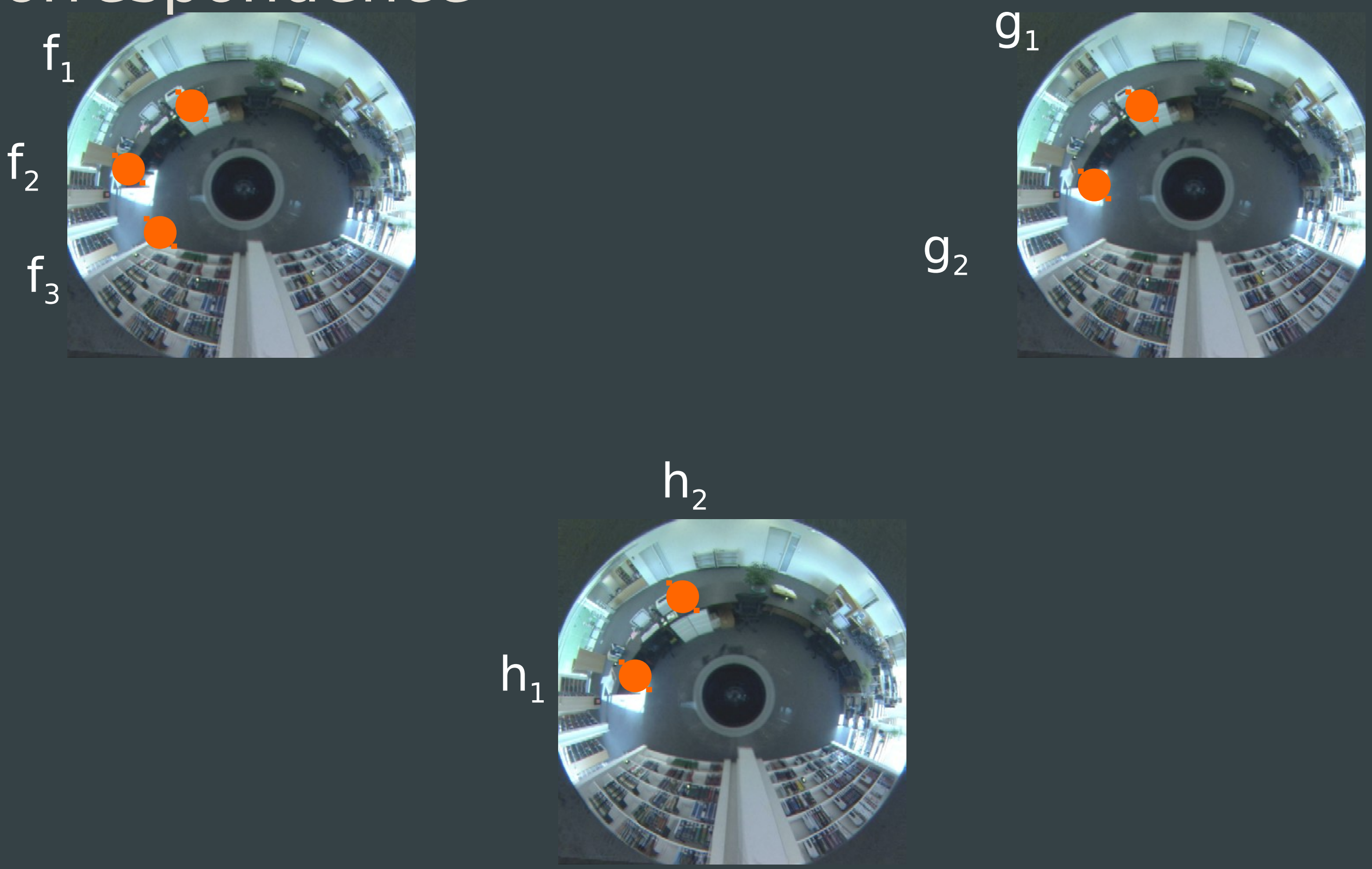
- The task is to choose the “best” subset of consistent correspondences between features of the source images
  - As an example, let’s choose a subset…



Floor plan

Relabeling

- Use a greedy graph-labeling algorithm to iteratively accept the next “best” potential correspondence



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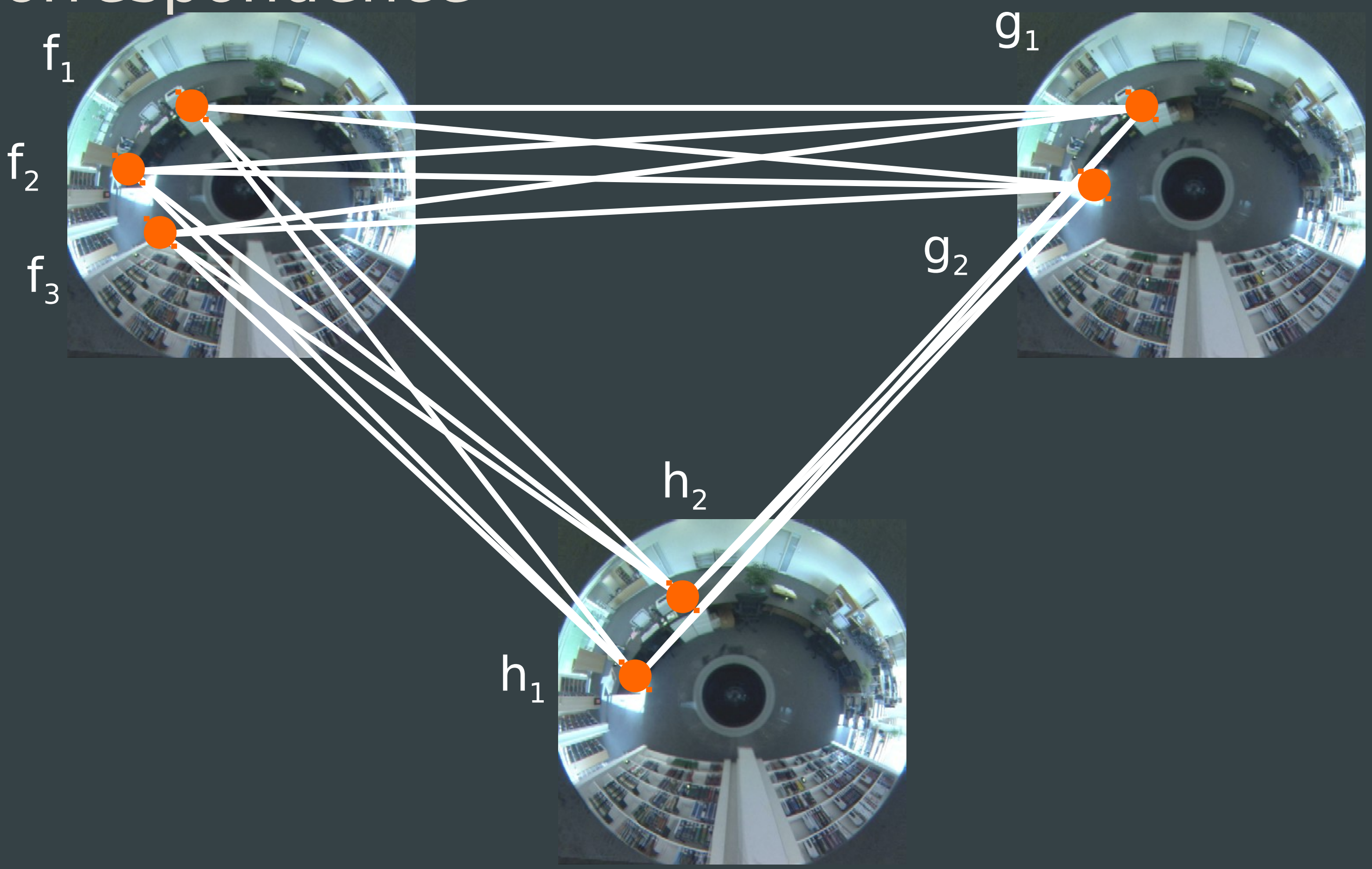

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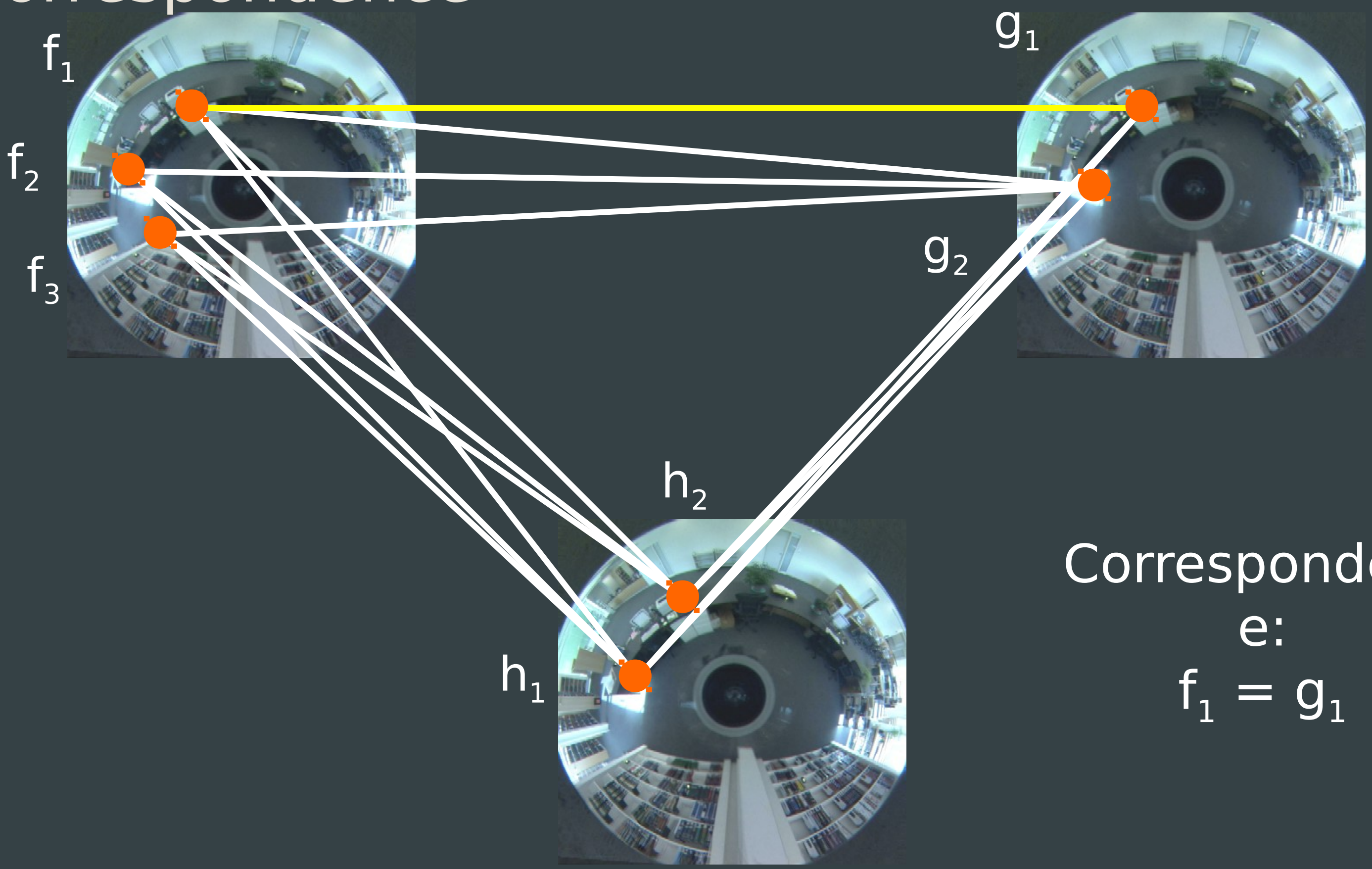

Correspondence:
$f_1 = g_1$

Relabeling

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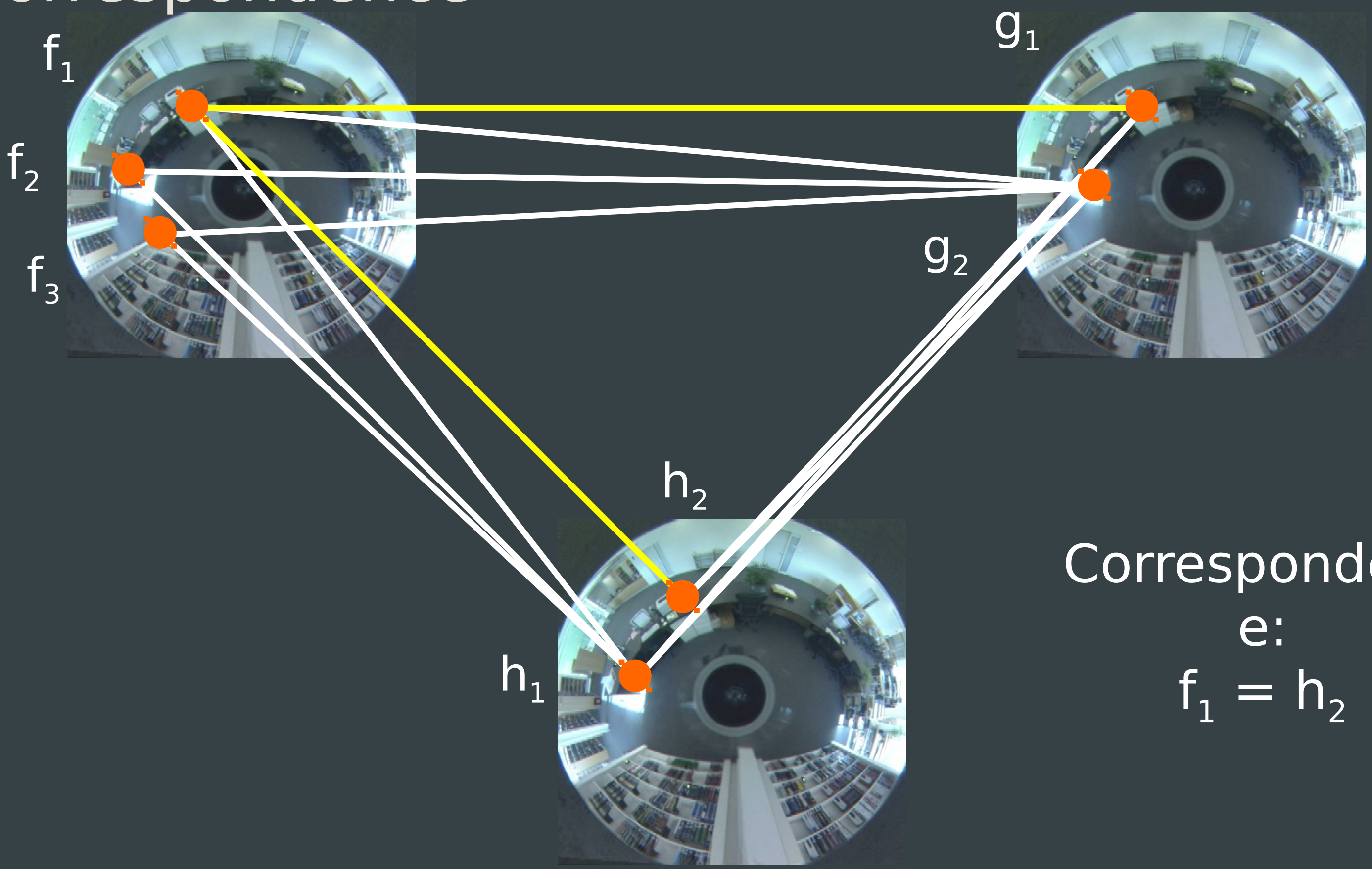

Correspondenc
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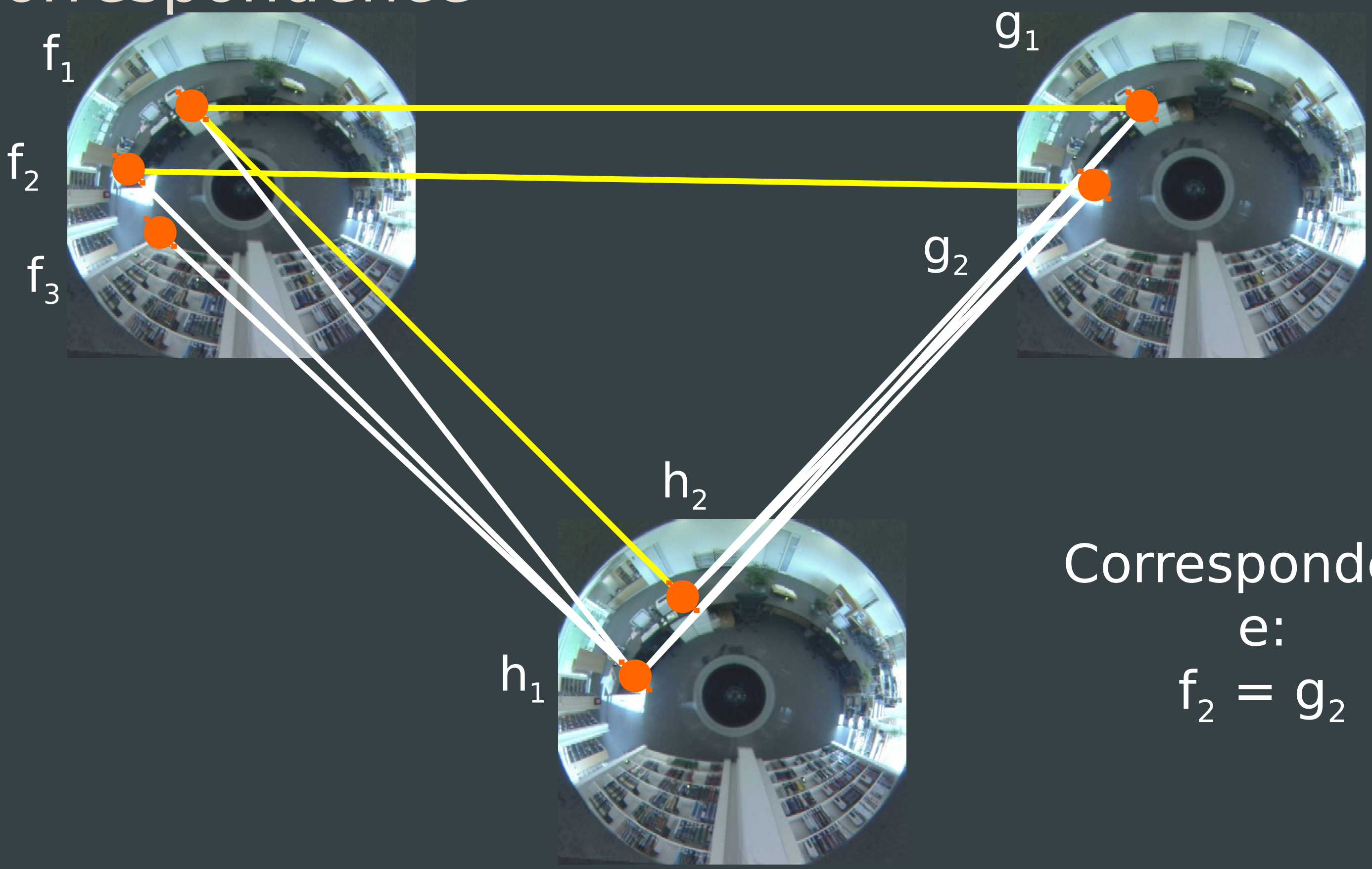

Correspondence:
$f_2 = g_2$

Relabeling

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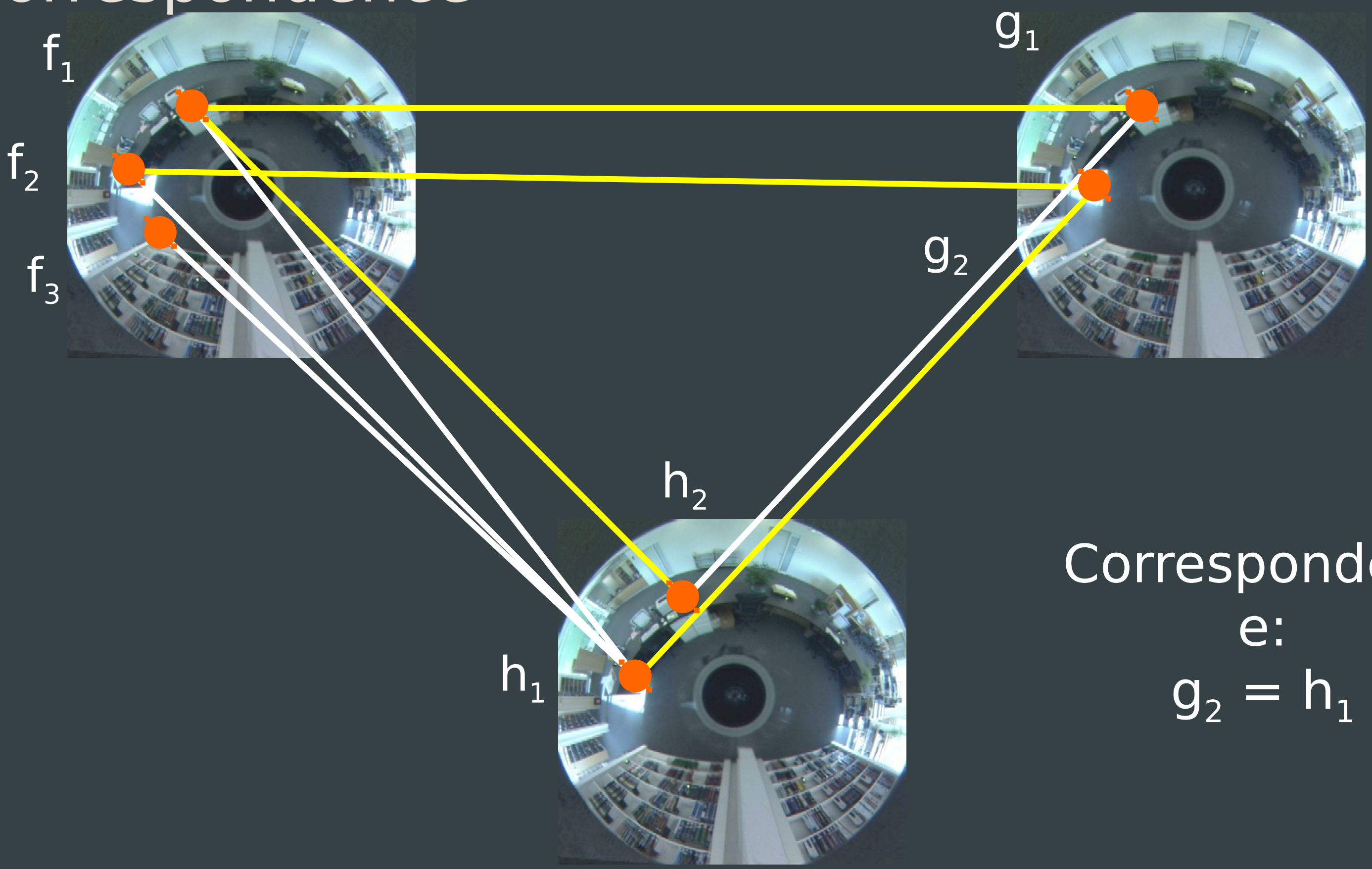

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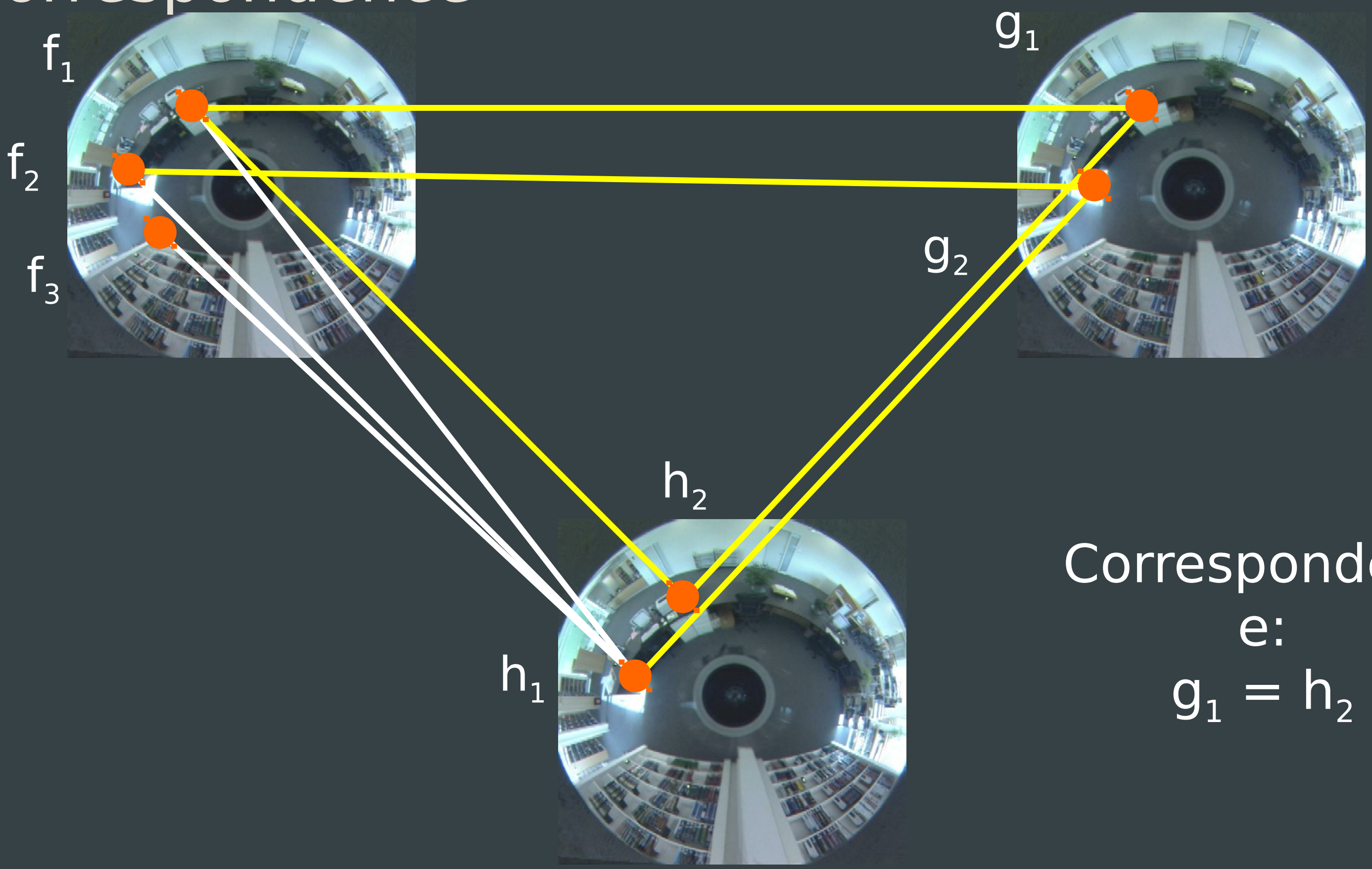

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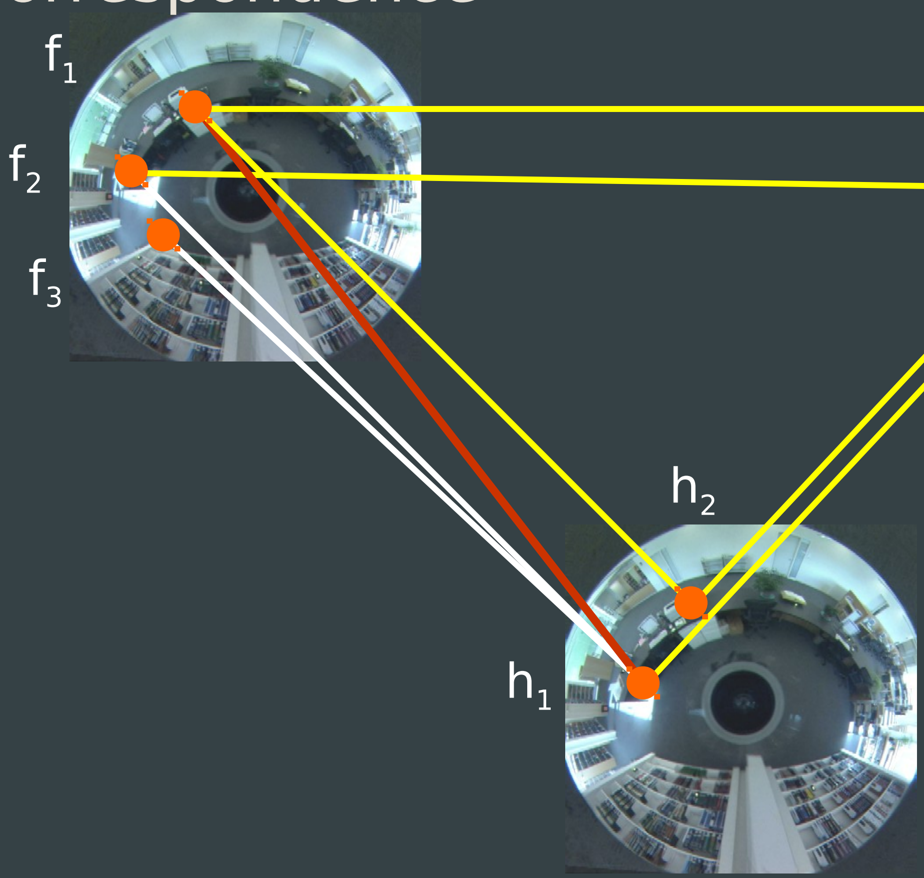

Correspondence:
$f_1 \neq h_1$

Relabeling

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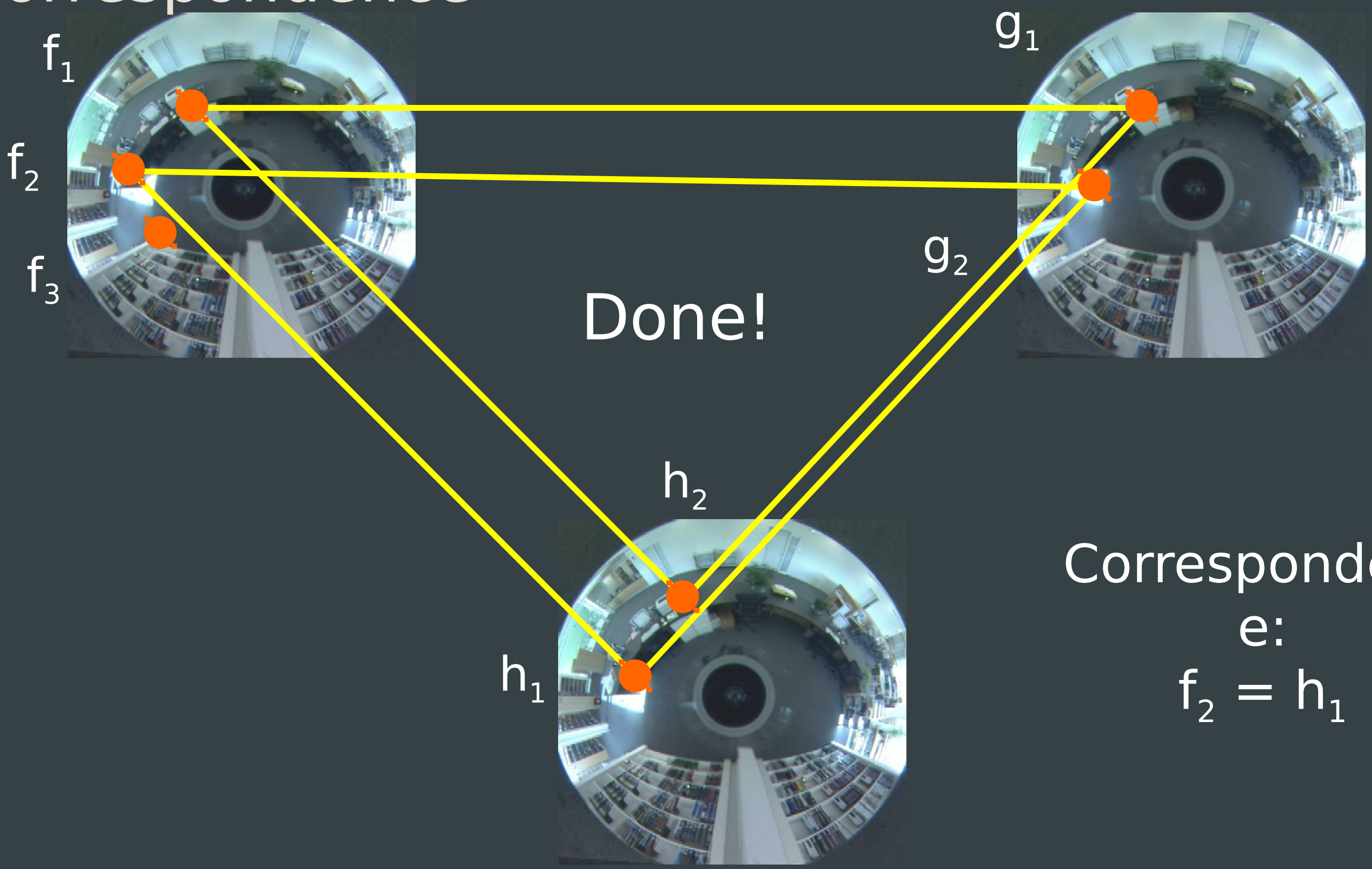

Correspondence:
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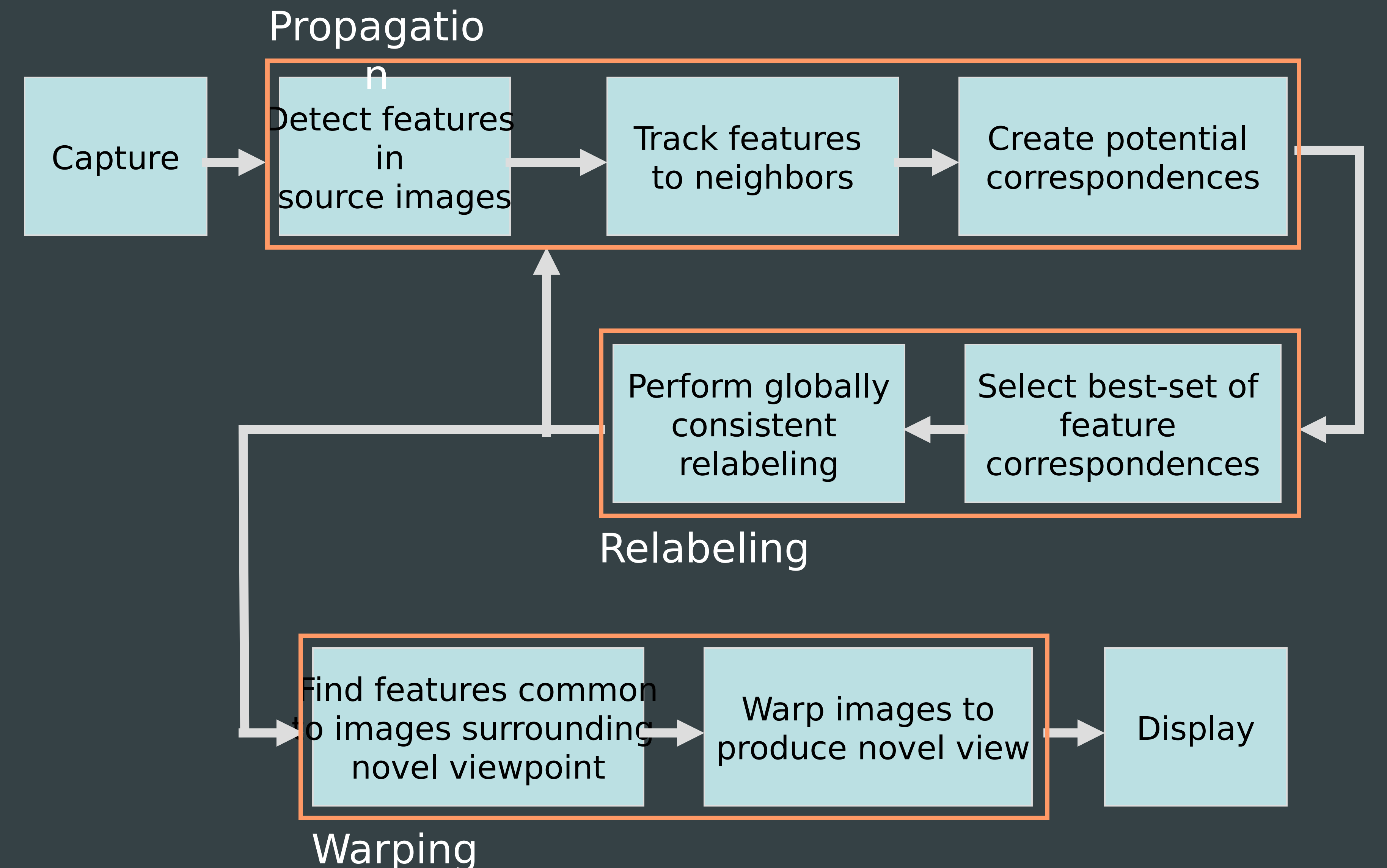
Feature Globalization Algorithm



Experimental Results

Experimental Results

- Bell Labs Museum
  - 1000 square ft
  - 9832 images
  - 2.2 inches spacing

- Princeton Library
  - 120 square ft
  - 1947 images
  - 1.6 inches spacing

- Personal Office
  - 30 square feet
  - 3475 images
  - 0.7 inches spacing

[Aliaga02]

Experimental Results

- System
  - C/C++ with OpenGL/GLUT
  - SGI Onyx2 with InfiniteReality2
  - Pentium IV 3 GHz with NVidia board
- Times
  - Reconstructions: 1024x1024 @ ~15-20Hz (SGI), @ ~60Hz (PC)
  - Number of initial features: ~1500 per image
  - Image-to-image tracking: 2-3 seconds
  - Preprocessing time: 4 to 30 hours

Rendering Results

- Use naïve image blending (no warping)
  - [Levoy96]
- Use a proxy to warp images
  - [Gortler96, Buehler01, Aliaga02]
- Use feature globalization

cylindrical projection

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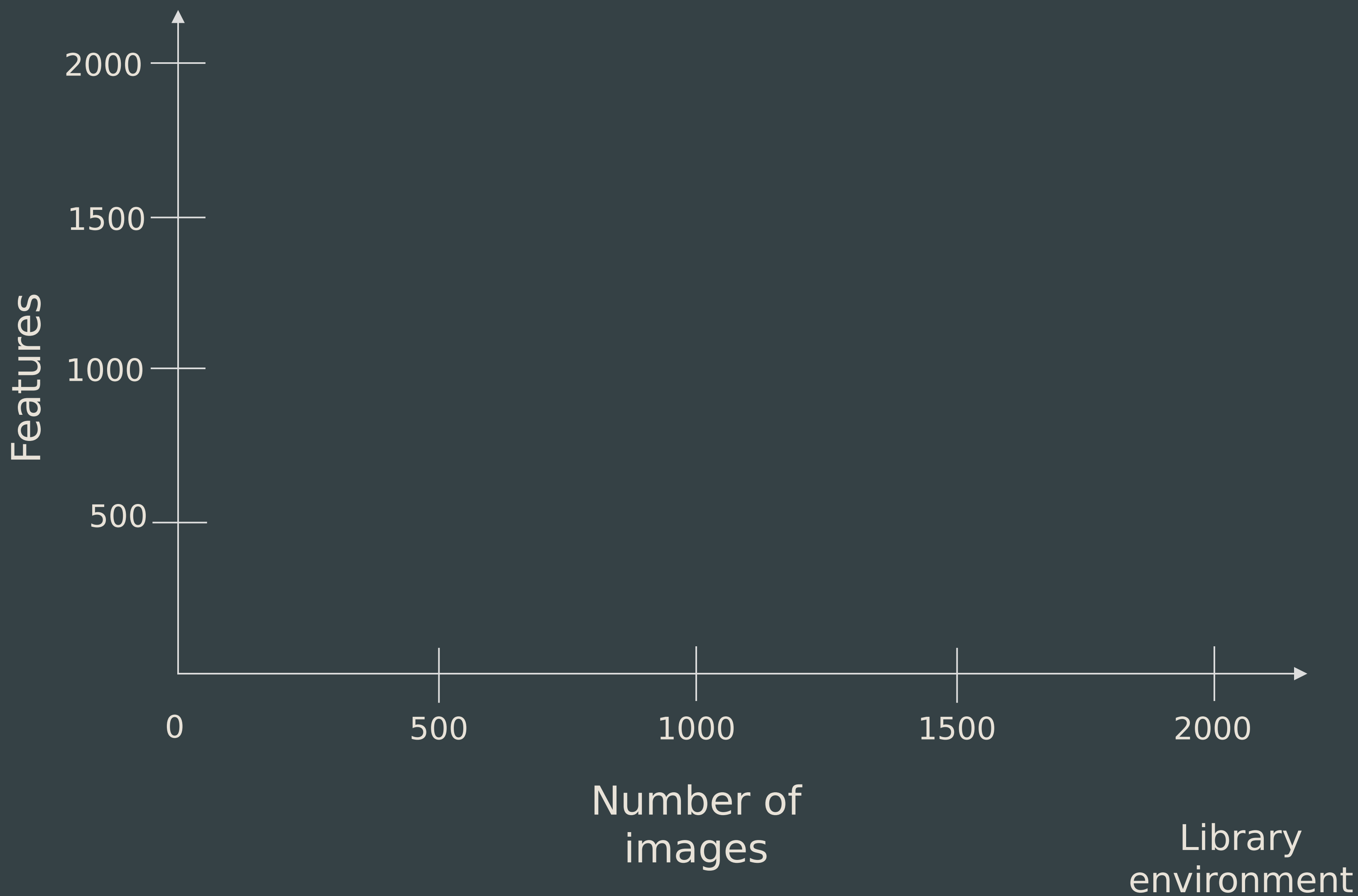
Rendering Results

- Video

Globalization Parameters

- Number of source images
  - An initial feature set is created at each source image
- Number of iterations
  - Each iteration does one step of propagation and relabeling
- Thresholds
  - Tracking quality
  - Feature quality

Globalization Parameters



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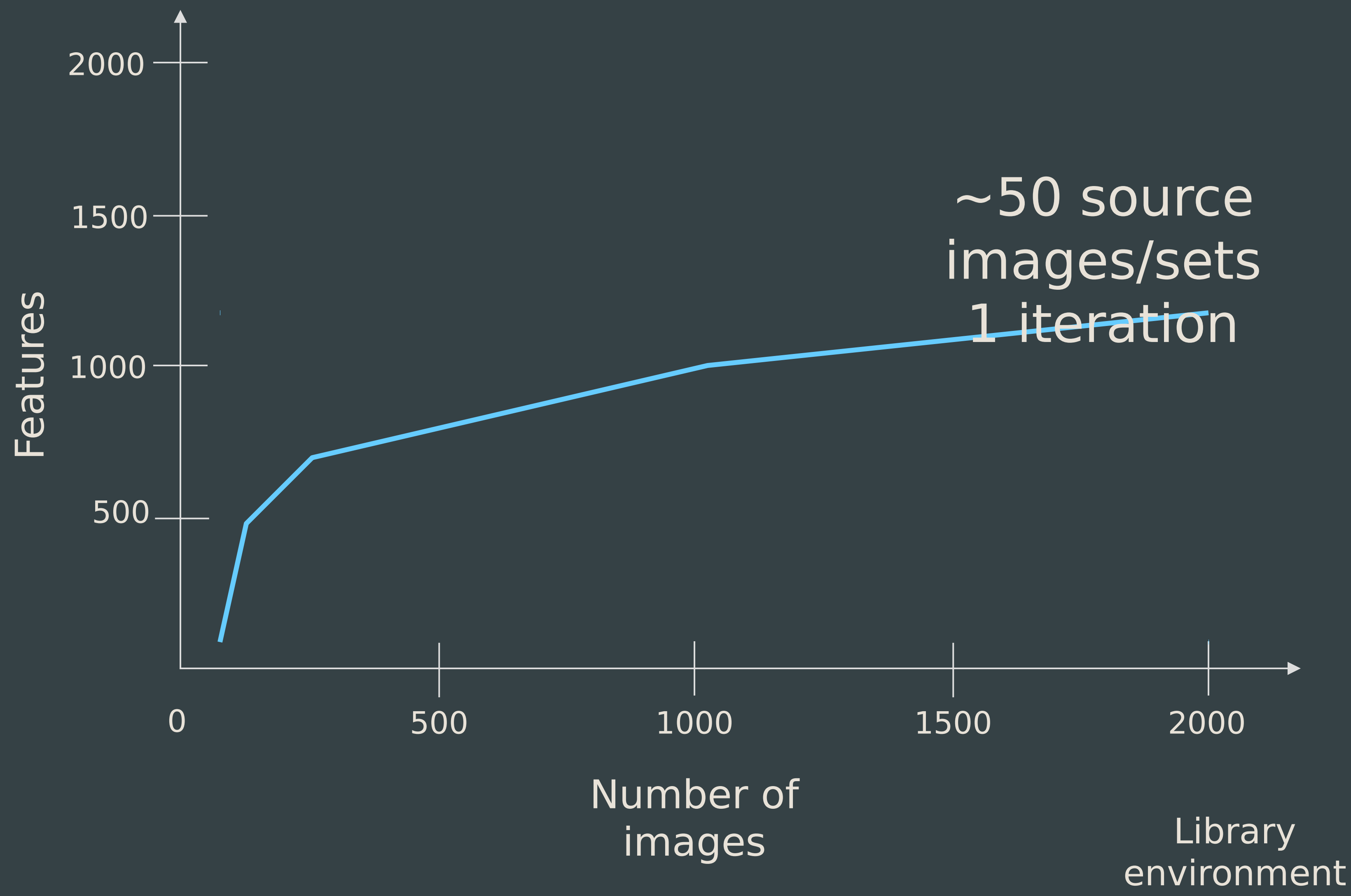

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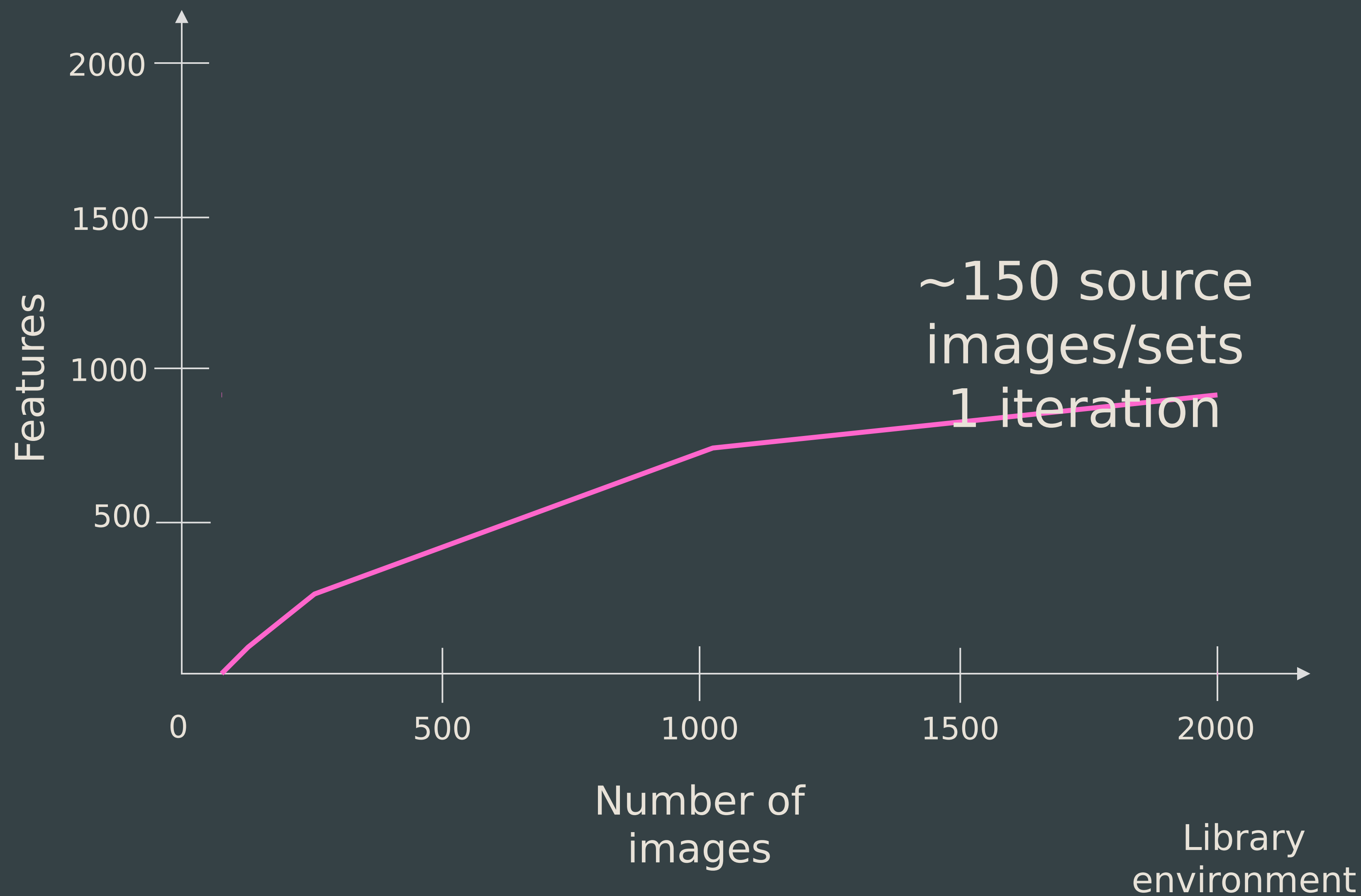

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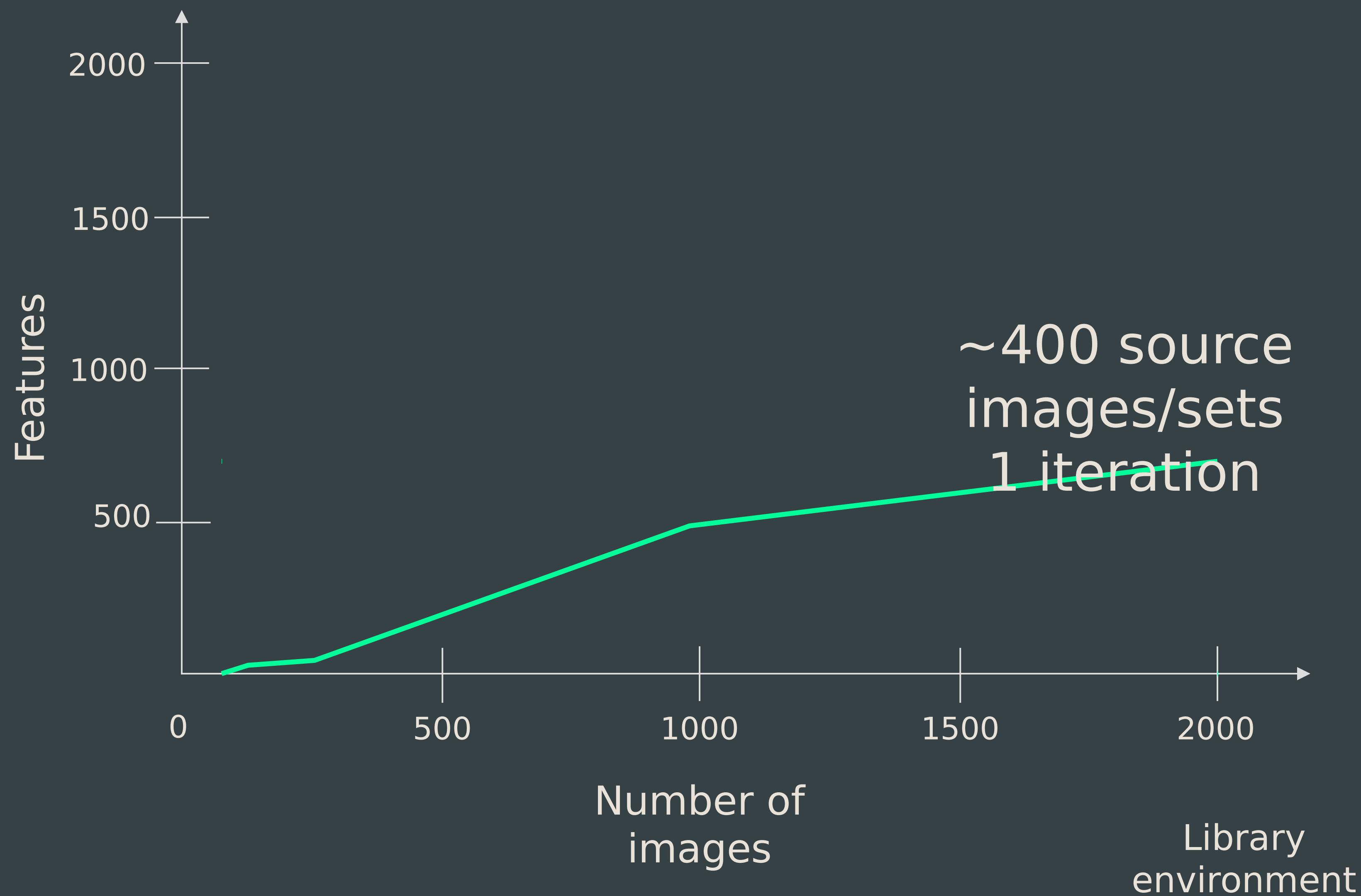

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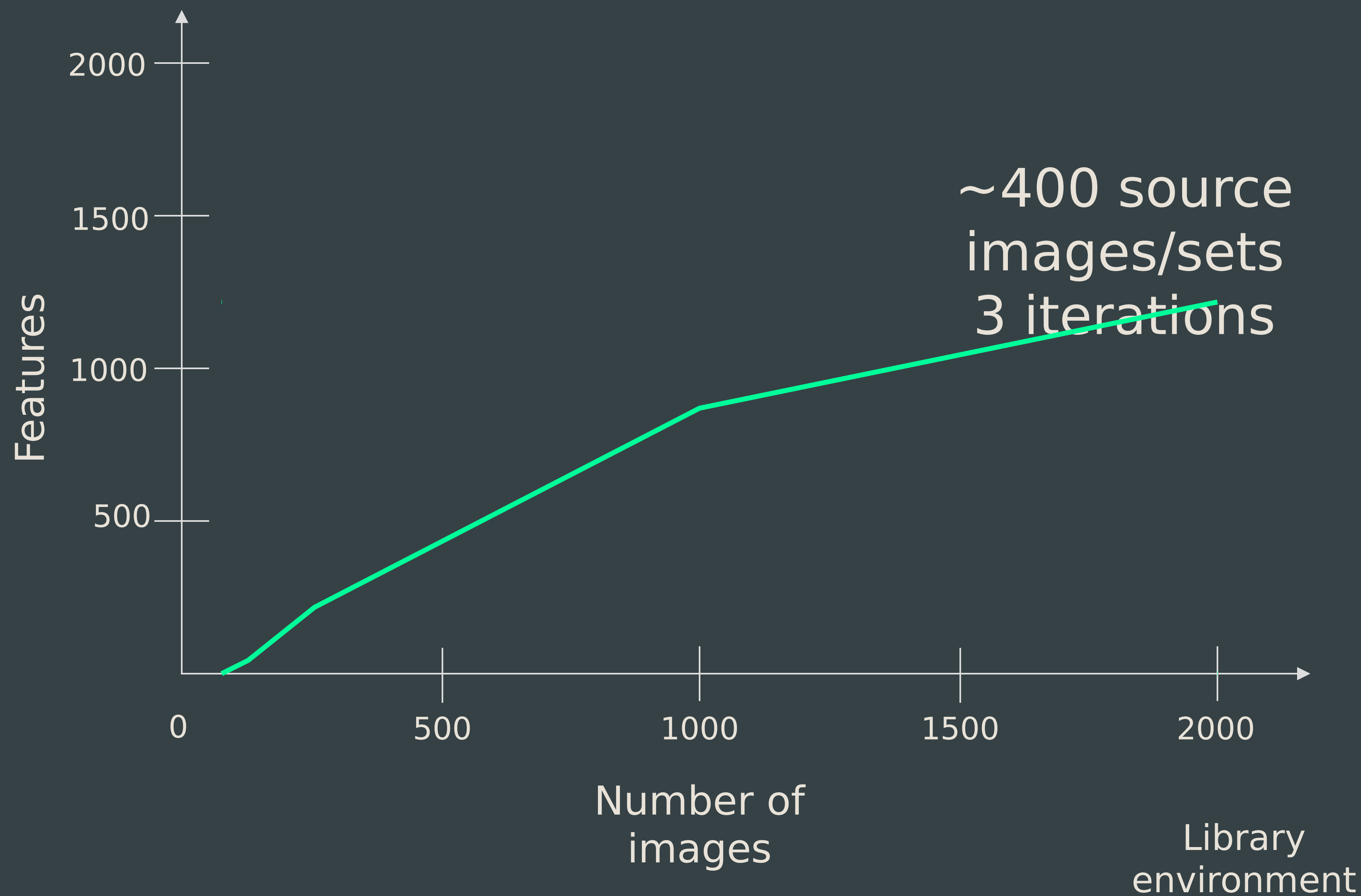

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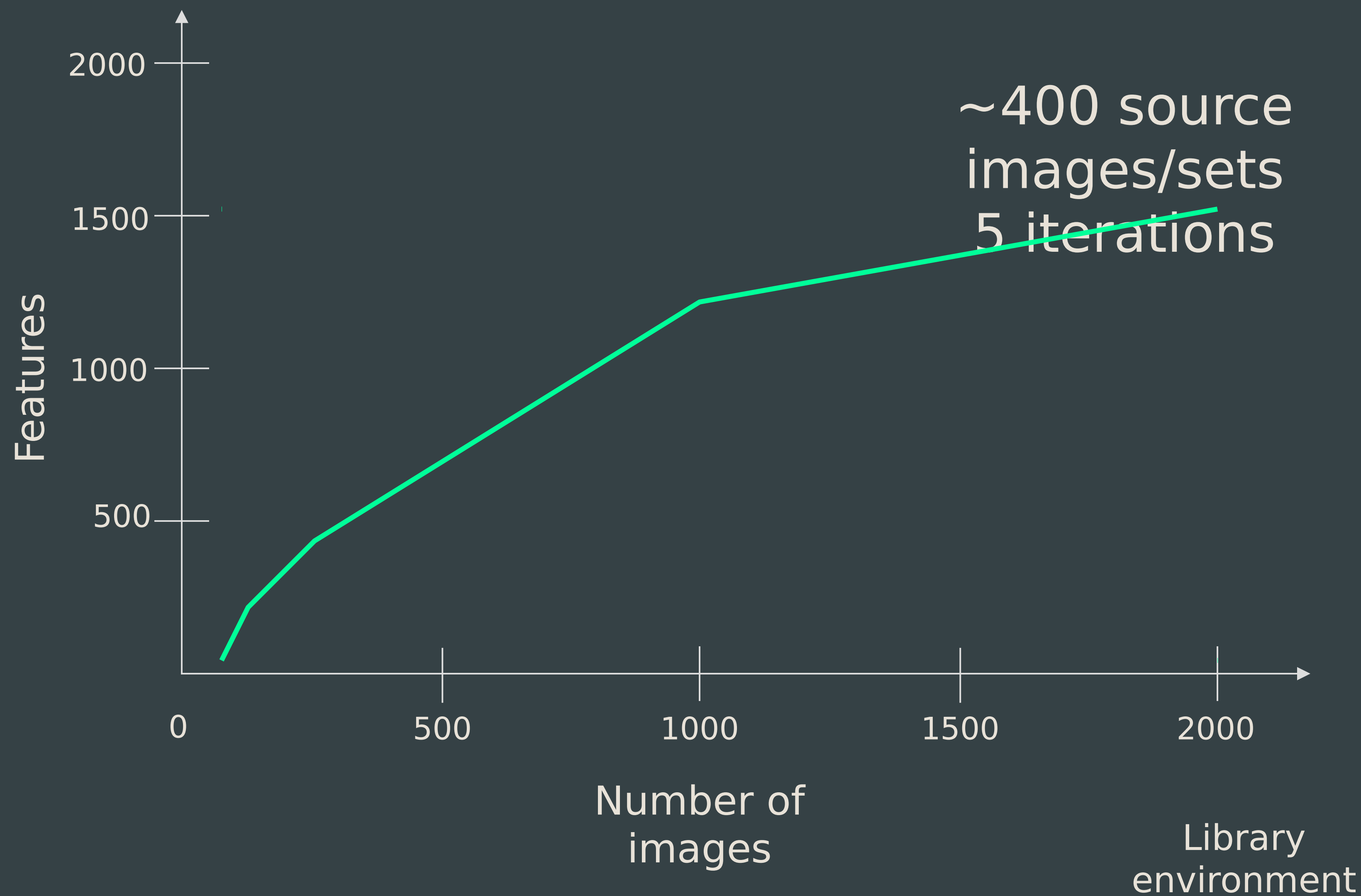

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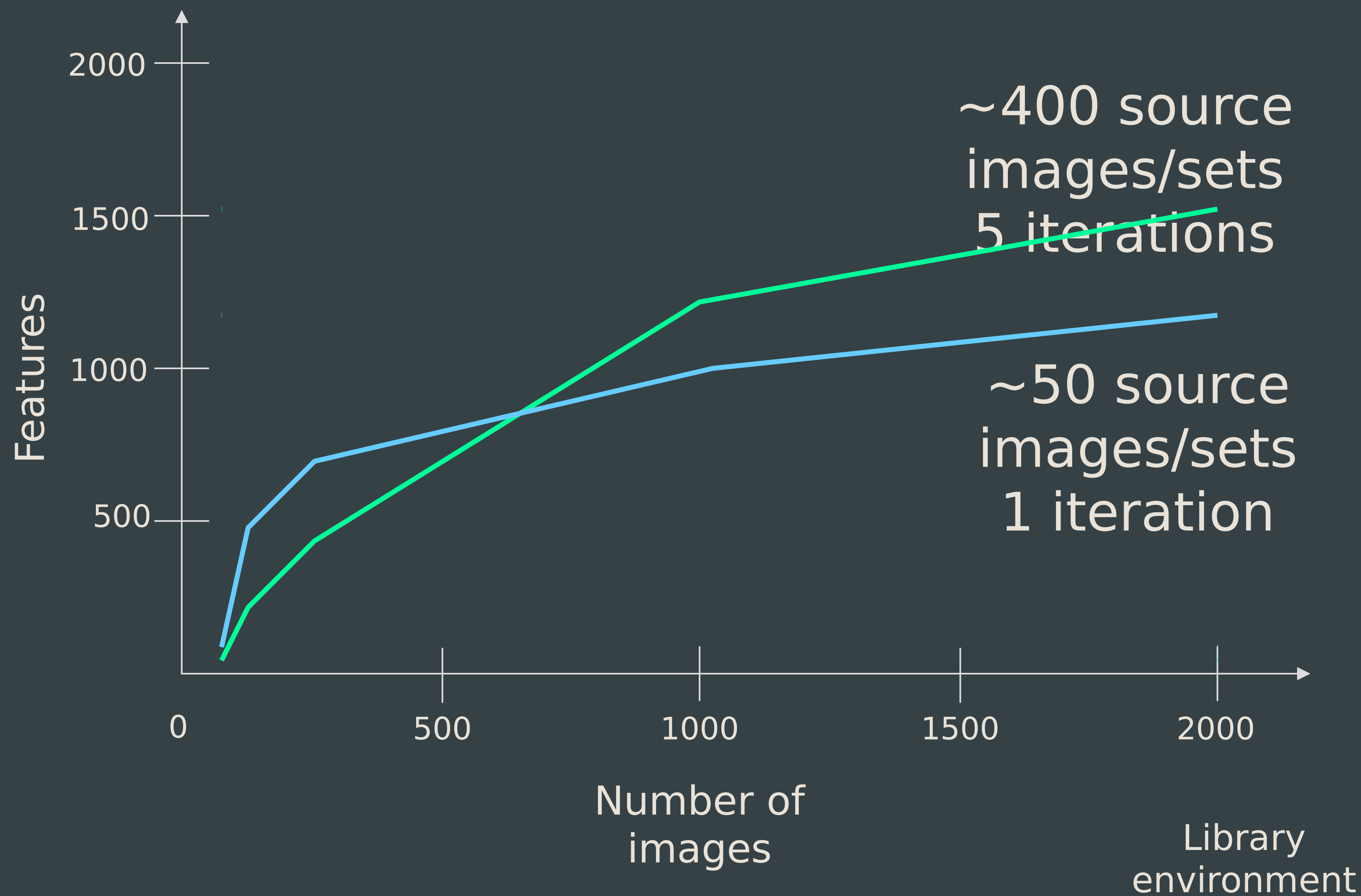
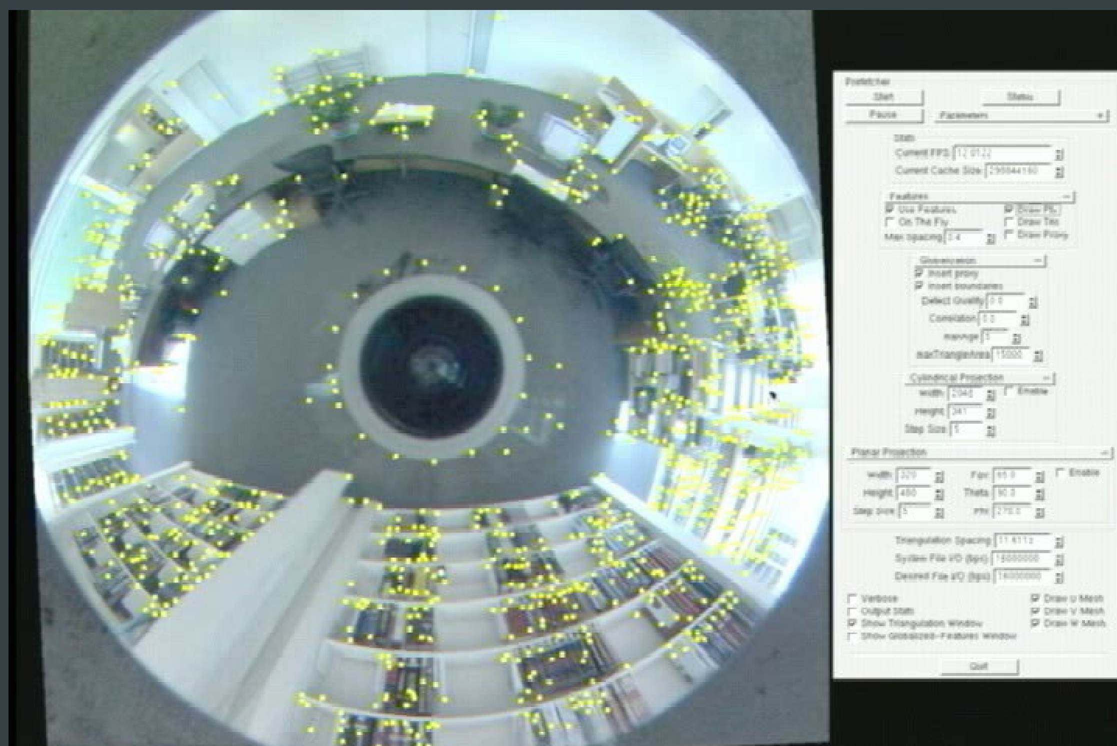


Globalization Parameters

- Feature globalization using more iterations outperforms using longer tracking sequences
  - 400 srcs/5 iterations is up to 2x better than 400 srcs/1 iteration
  - More iterations makes globalization less sensitive to number of source images (because complete globalization is approached)

Current Limitation

- Although not very noticeable visually, common features found on the fly can change significantly from one set of reference images to another



Conclusions

- Improved feature tracking
  - Redundancy of dense sampling exploited to achieve longer/better feature tracking
- Globally consistent feature labeling
  - Able to produce a globally-labeled set of features for a large dense collection of images
- High quality image reconstructions
  - Significantly improved imagery as compared to previous image-based rendering algorithms

Future Work

- Use feature globalization for compression
- Use (real-time) feedback to guide capture and improve globalization and reconstruction quality
- Use features for 3D reconstruction of the scene

Acknowledgments

- We are grateful to Sid Ahuja, Multimedia Research Lab VP at Bell Labs, Bob Holt, and Steve Fortune

Thank you!

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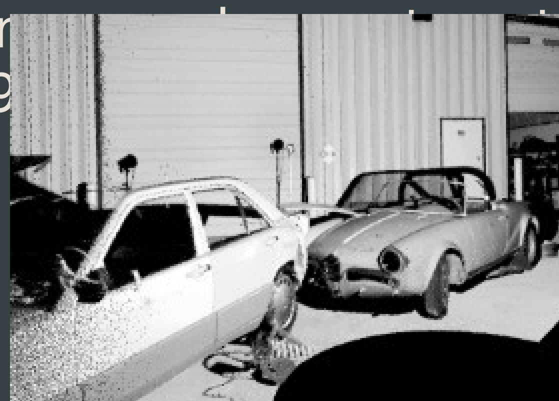
ACM SIGGRAPH 2003 Symposium on Interactive 3D Graphics

Possible Rendering Approaches

- Naive image blending
  - Produces blurry images if not sampled very densely [Levoy96]
- Proxy-based warping
  - Quality depends on accuracy of proxy [Gortler96, Buehler01]
- Depth-based warping
  - Requires dense physical measurements [Nyland01] or dense cor… …imate depth [Chen93, McMillan9…
- Or…



Feature-based Warping

- Combine a feature tracking method and a global labeling algorithm in order to create correspondences over a wide viewpoint range and produce novel views in real-time

- ---------needs works----------
- Diff from Pollefeys, where?

Our Approach: Feature Globalization

- Combine a feature tracking method and a global labeling algorithm in order to create correspondences over a wide viewpoint range and produce novel views in real-time

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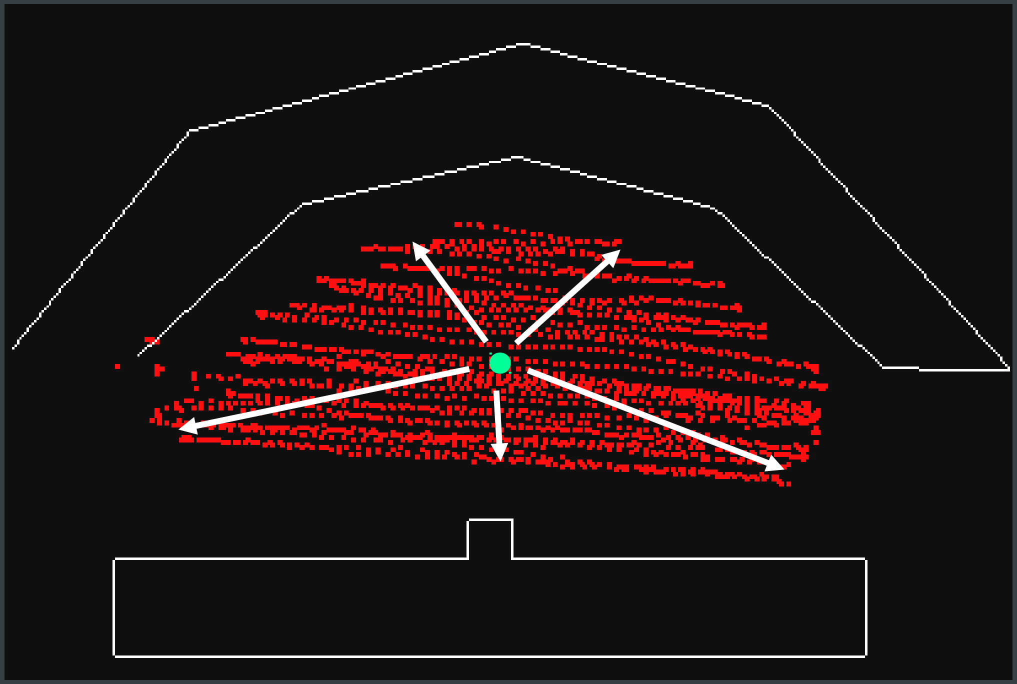
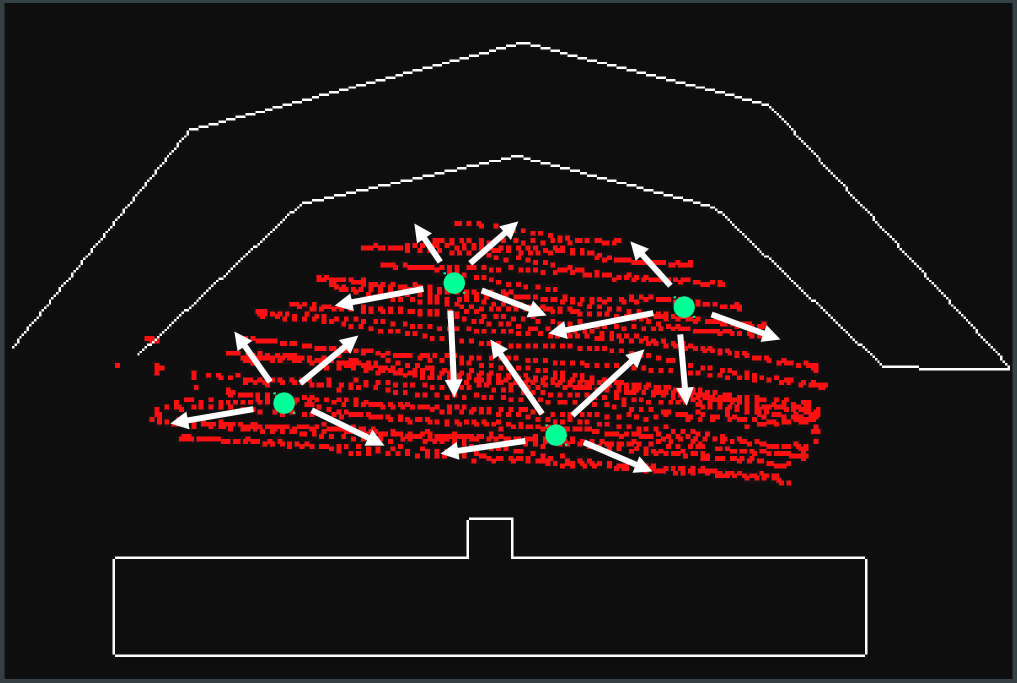
Feature Globalization

- Simplest algorithm is to detect (corner) features in one source image and track features to all other images
  - Fails because features quickly become lost



Feature Globalization

- Instead, detect features in <u>many</u> source images and track to nearby images
  - Features are only tracked short distances
  - Matching creates correspondences over large ranges



IBR Resampling Goals

- High-Quality
  - Prevent ghosting and blurring at all times
  - Reliable across whole environment
  - Independent from accurate 3D knowledge of environment
- Automatic
  - To support large environments, method must be automatic
- Real-time
  - Create novel views at high frame rates
- Flexibility (??)
  - To support hierarchies and prefetching of large models, method must generate novel views with whatever samples are in cache

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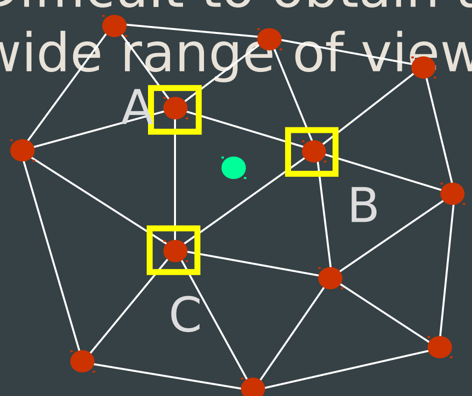
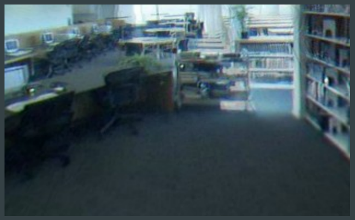
  - Quality depends on accuracy of proxy [Gortler96, Buehler01]
- Feature-based warping
  - Difficult to obtain a large number of features across a wide range of viewp



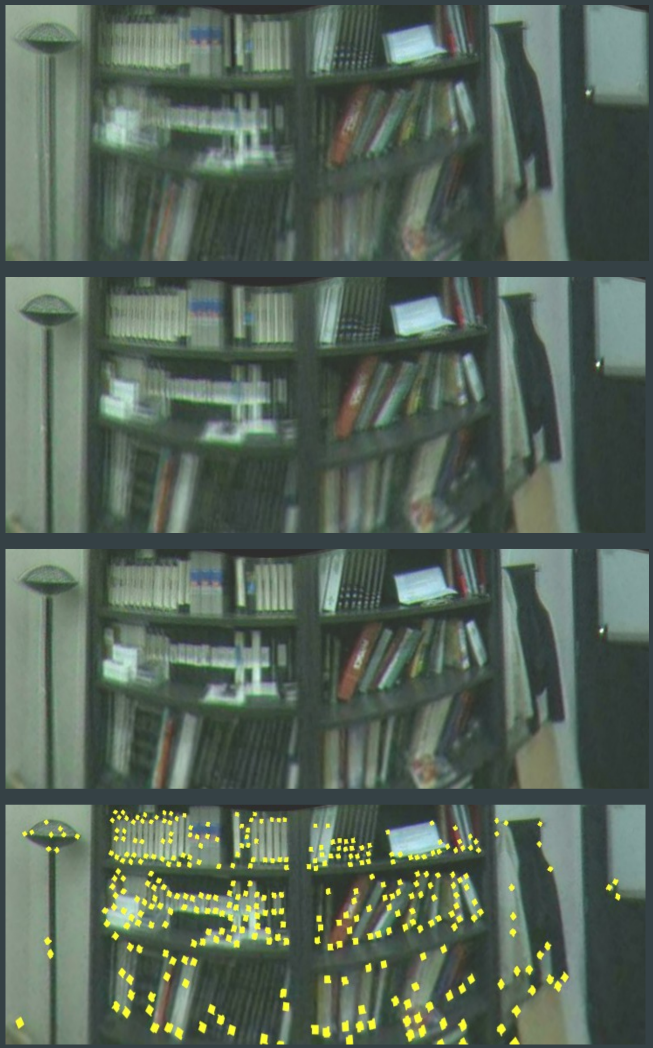

A


B


C

Interactive Image-Based Rendering Using Feature Globalization

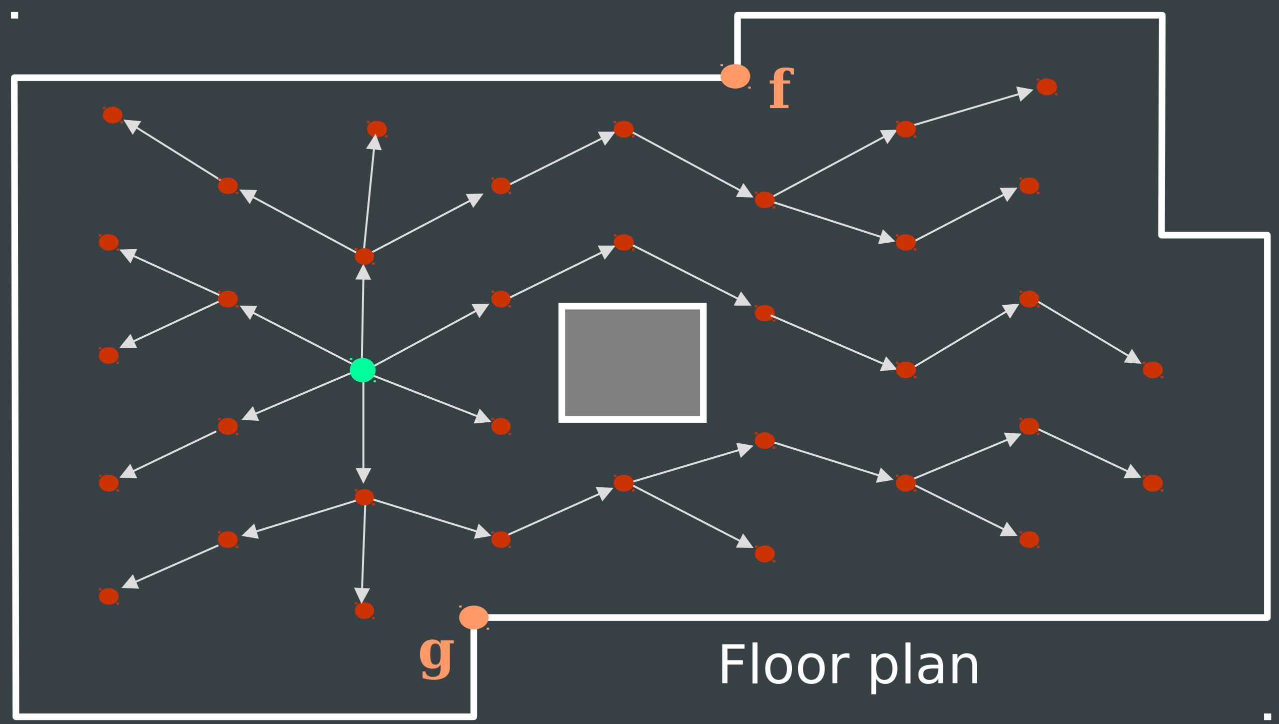
- Acknowledgments:
  - We are grateful to Sid Ahuja, Multimedia Research Lab VP at Bell Labs, Bob Holt, and Steve Fortune
  - NSF CAREER ????



Thank you!

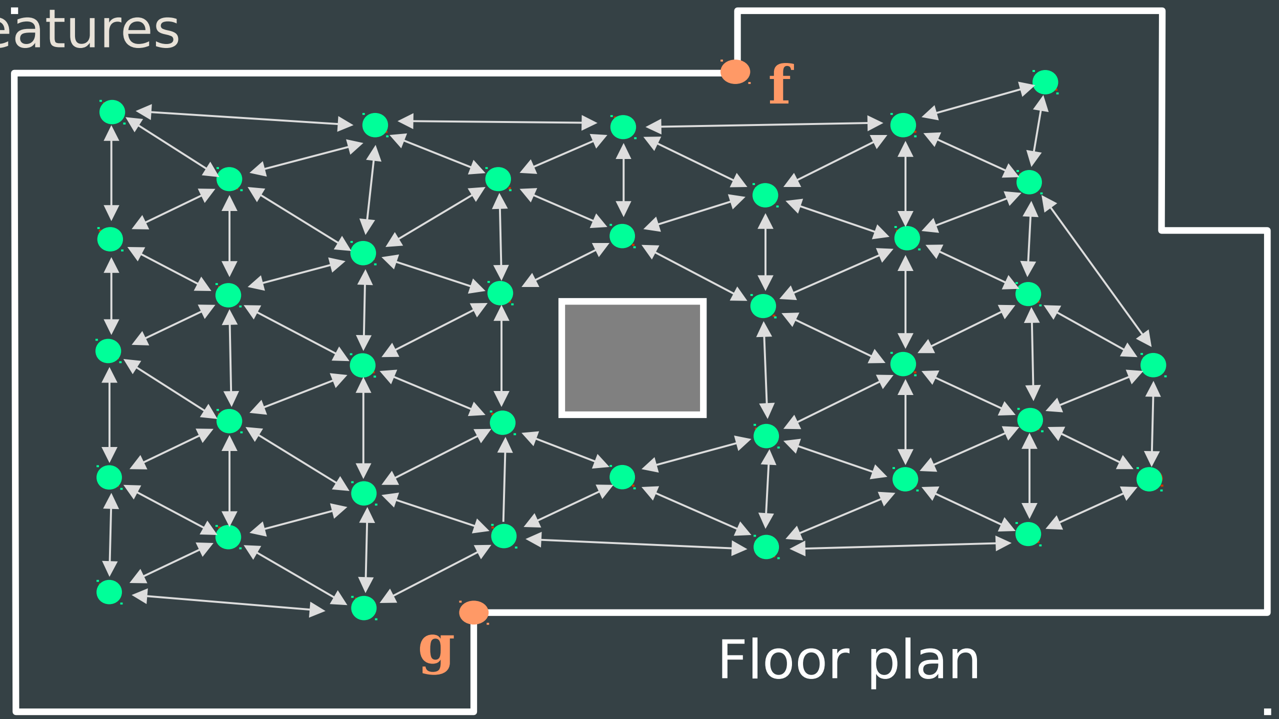
Feature Globalization

- Create a global set of features using a dense set of captured images (over a plane)
  - If one image is a source image, *feature tracking limitations* causes features to be lost



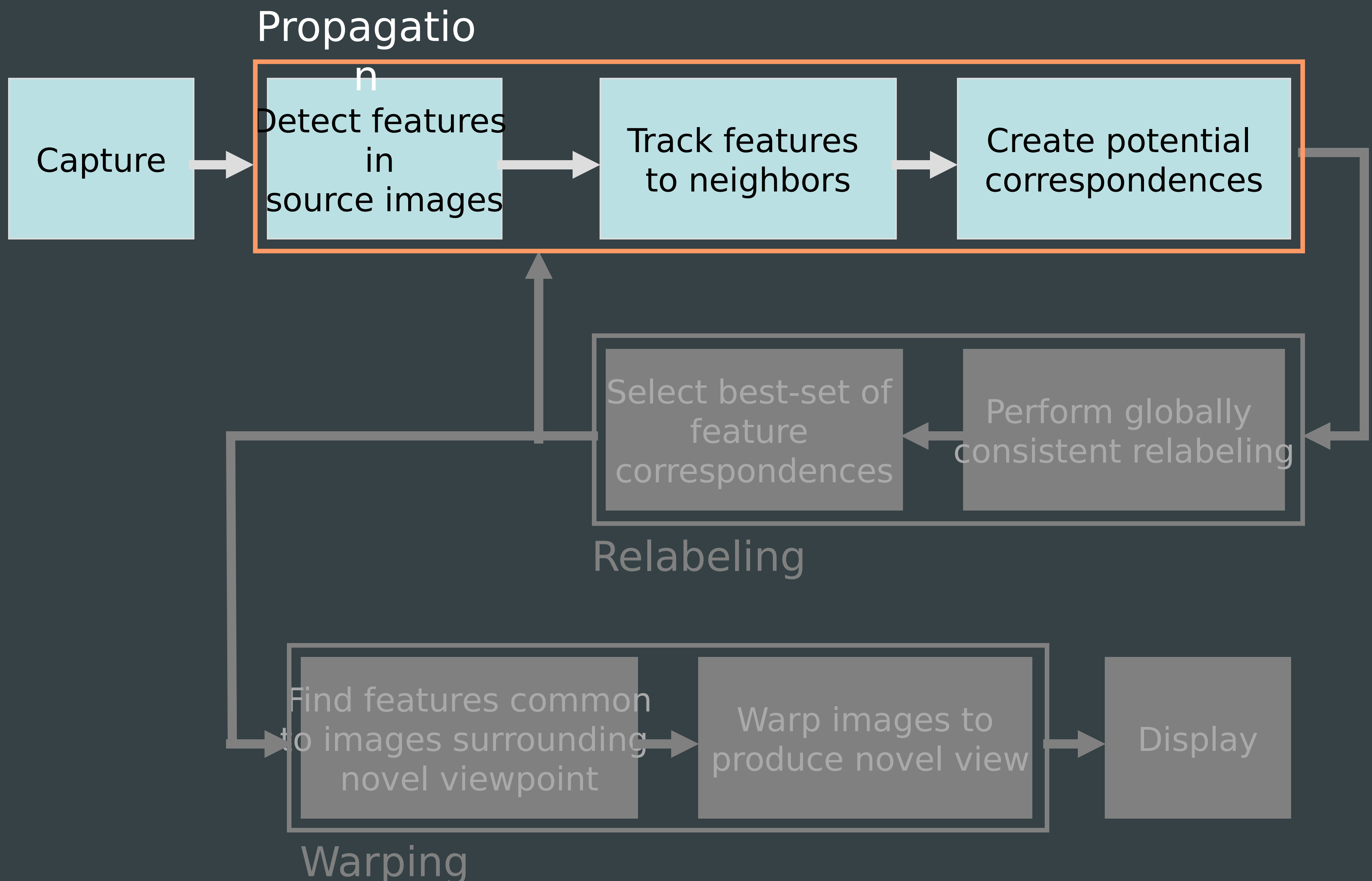
Feature Globalization

- Create a global set of features using a dense set of captured images (over a plane)
  - If every image is a source image, *feature detection limitations* cause neighboring images to have different features



Floor plan

Feature Globalization Algorithm



Feature Globalization Algorithm